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COMPETING FOR ATTENTION: A MATHEMATICAL MODEL OF CONTENT VISIBILITY AND AUDIENCE ENGAGEMENT IN ONLINE MEDIA

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ABSTRACT

In the contemporary digital media landscape, content creators and platform curators face the challenge of understanding why certain articles achieve viral reach while others remain largely invisible. This study applies the Lotka-Volterra predator-prey model an ecological framework traditionally used to describe population dynamics to analyse the competitive engagement patterns between high-engagement and low-engagement articles on Mashable, a major digital media platform. Drawing on the Online News Popularity dataset, which encompasses 39,644 articles with 58 predictive features including keyword density, multimedia elements, sentiment polarity, and publication timing, we derive four key interaction parameters (α, β, δ, γ) that govern engagement growth, competitive suppression, conversion, and decay. Stability analysis of the resulting differential equation system reveals four equilibrium points, of which the interior equilibrium exhibits purely imaginary eigenvalues ($\lambda = \pm 31.07i$), indicative of sustained oscillatory dynamics. These cycles mirror the rhythmic patterns observed in broadcast scheduling and editorial curation, where viral content surges suppress background coverage until audience attention redistributes. The findings demonstrate that mathematical ecology offers a novel analytical lens for media professionals, content strategists, and digital arts practitioners seeking to understand and optimise audience engagement over time.

Keywords: Content Popularity Dynamics, Engagement Modelling, Lotka-Volterra Equations, Digital Media Analytics, Audience Engagement, Predator-Prey Model

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1. INTRODUCTION

Digital media platforms such as Mashable operate within an intensely competitive attention economy, where thousands of articles are published daily across topics ranging from technology and entertainment to culture and lifestyle. The visibility of any given piece of content is neither stable nor guaranteed; instead, it fluctuates in response to platform algorithms, reader behaviour, trending topics, and the simultaneous presence of competing content. Understanding these fluctuations is of direct relevance to digital content creators, media curators, and visual communication professionals who must make strategic decisions about what to publish, when to publish, and how to position content for maximum audience reach.

The dynamics of content popularity in digital environments bear a striking resemblance to the population dynamics studied in theoretical ecology. Just as predator and prey populations interact in a competitive ecosystem with each species' growth constrained and enabled by the presence of the other high-engagement and low-engagement articles compete for a finite pool of reader attention. Articles that achieve high engagement (measured by social shares) benefit from algorithmic amplification, which drives further visibility at the expense of lower-performing content. Conversely, when viral articles fade, lower-engagement content gains the opportunity to fill the resulting attention gap.

This study models these dynamics using the Lotka-Volterra predator-prey equations, a classical system of differential equations originally formulated to describe biological population cycles (Volterra, 1926). We apply this framework to the Online News Popularity dataset from Mashable, parameterising the model using article-level features such as keyword density, image count, sentiment polarity, and publication timing. Through mathematical formulation and stability analysis, we demonstrate that engagement cycles in digital media exhibit the same oscillatory neutrally stable behaviour predicted by Lotka-Volterra theory. The findings carry practical implications for content strategy in digital arts and media production contexts, providing a quantitative basis for optimising publication scheduling and content mix. Joy (2026)

2. METHOD

2.1. DATASET AND FEATURE SELECTION

The study employs the Online News Popularity dataset (Fernandes et al., 2015), which aggregates metadata from 39,644 articles published on Mashable over a two-year period. The dataset includes 58 predictive features and two non-predictive attributes (URL and publication timedelta). The target variable is the number of social shares an article receives, used here as a proxy for audience engagement. Key features informing the model parameters include: number of keywords (num_keywords), image count (num_imgs), hyperlink count (num_hrefs), global sentiment polarity (global_sentiment_polarity), subjectivity score (global_subjectivity), maximum keyword shares (kw_max_max), average keyword shares (kw_avg_avg), weekend publication flag (is_weekend), and article age in days (timedelta).

2.2. ENGAGEMENT CLASSIFICATION

Articles were classified into two engagement categories based on share count percentiles. Articles above the 75th percentile of share counts were designated as high-engagement (predator population, y), and those below the 25th percentile were designated as low-engagement (prey population, x). This percentile-based classification creates two clearly delineated groups whose interaction can be modelled dynamically.

2.3. THE LOTKA-VOLTERRA FRAMEWORK

The classical Lotka-Volterra predator-prey system is expressed as:

$$dx/dt = \alpha x - \beta xy$$

$$dy/dt = \delta xy - \gamma y$$

where x represents the count of low-engagement articles (prey), y represents the count of high-engagement articles (predators), α is the intrinsic growth rate of low-engagement articles, β is the suppression rate imposed on low-engagement articles by high-engagement competition, δ is the rate at which low-engagement articles are converted to high-engagement status, and γ is the natural decay rate of high-engagement articles over time.

2.4. PARAMETER DERIVATION

The four parameters were derived from dataset features as weighted linear combinations reflecting the known drivers of engagement in digital media contexts:

α (prey growth rate) = 0.2 × num_keywords + 0.2 × num_imgs + 0.1 × global_sentiment_polarity

β (predation rate) = 0.15 × kw_max_max + 0.15 × kw_avg_avg + 0.1 × global_subjectivity

δ (conversion rate) = 0.1 × num_hrefs + 0.2 × is_weekend

γ (decay rate) = 0.25 × timedelta − 0.1 × global_sentiment_polarity

These weightings reflect the theoretical assumption that keyword richness and imagery drive baseline article growth, that competition from highly shared articles depresses lower-performing content, that internal linking and weekend publication timing promote conversion to viral status, and that older articles with neutral sentiment naturally decline in engagement.

2.5. STABILITY ANALYSIS

Equilibrium points of the system were identified by setting both differential equations to zero. The resulting four equilibrium points are: (0, 0), (0, α/β), (γ/δ, 0), and (γ/δ, α/β). The stability of each point was assessed by linearising the system via the Jacobian matrix:

$$J = [\ (\alpha - \beta y)\quad (-\beta x)\ ;\ (\delta y)\quad (\delta x - \gamma)\ ]$$

Eigenvalues were computed at each equilibrium to classify stability behaviour.

3. RESULTS AND DISCUSSION

3.1. ESTIMATED PARAMETERS

Applying the feature-weighted formulas to the Mashable dataset yielded the following parameter estimates:

α (Prey Growth Rate): 10.6490

β (Predation Rate): 0.0324

δ (Conversion Rate): 0.2292

γ (Predator Decay Rate): 90.6305

The notably high γ value relative to α reflects the empirical observation that virality on Mashable is short-lived: high-engagement articles lose their amplified reach rapidly, while the underlying pool of lower-engagement content persists and regenerates steadily. The low β value indicates that, while competitive suppression exists, individual viral articles do not catastrophically eliminate low-engagement content they merely suppress it temporarily, consistent with patterns observed in broadcast media scheduling (Liu et al., 2021).

3.2. EQUILIBRIUM ANALYSIS

Stability assessment of the four equilibrium points produced the following results:

(0, 0): The trivial equilibrium yields eigenvalues $\lambda_1 = \alpha > 0$ and $\lambda_2 = -\gamma < 0$, classifying it as a saddle point. This is ecologically meaningful: total extinction of all content is unstable because the publishing ecosystem continuously generates new articles.

(0, α/β): Eigenvalues $\lambda_1 = 0$ and $\lambda_2 = -\gamma$ indicate semi-stability. A platform populated only by high-engagement content with no low-engagement base is unsustainable it collapses toward the trivial state.

(γ/δ, 0): Eigenvalues $\lambda_1 = \alpha > 0$ and $\lambda_2 = 0$ indicate instability. A system with only low-engagement content and no viral articles will not remain in that state; some articles will eventually convert.

(γ/δ, α/β): The non-trivial interior equilibrium the most ecologically significant point produces eigenvalues $\lambda = \pm i\sqrt{(\alpha\gamma)} = \pm 31.07i$. These purely imaginary eigenvalues indicate a centre, confirming neutral stability and predicting sustained oscillatory dynamics rather than convergence to a fixed state or divergence to extinction.

3.3. ENGAGEMENT DYNAMICS AND OSCILLATORY PATTERNS

Time-series simulation of the Lotka-Volterra system using the estimated parameters reveals recurring cycles of engagement surge and recovery. When low-engagement articles accumulate in sufficient numbers, they provide the raw material for viral conversion: social sharing, algorithmic surfacing, and audience discovery drive a subset of articles into the high-engagement category. This influx of viral content then suppresses the base population of low-engagement articles, as the finite audience pool is captured by high-engagement material. As viral articles age and decay losing algorithmic priority and reader novelty low-engagement content recovers, beginning the next cycle.

These oscillatory patterns are directly analogous to phenomena well-known in media and performance contexts. In broadcast scheduling, the saturation of a popular programme format leads to audience fatigue and declining ratings, creating space for new formats to emerge. In live performance arts, the concentration of audience attention on blockbuster productions temporarily diminishes attendance at smaller or experimental works, until the blockbuster run concludes and audiences diversify again (Hollebeek & Macky, 2019). The Lotka-Volterra model provides a mathematical vocabulary for describing these cycles with precision.

The high amplitude of high-engagement peaks in the simulation reflecting the explosive but brief nature of viral reach contrasts with the lower but more sustained presence of low-engagement content. This asymmetry has practical implications: while viral content yields maximal short-term visibility, a consistent foundation of moderate-quality content ensures platform vitality between viral cycles.

3.4. IMPLICATIONS FOR DIGITAL MEDIA AND CONTENT STRATEGY

From a media production and content strategy perspective, the oscillatory model suggests several actionable insights. First, the timing of content release relative to the current phase of the engagement cycle can significantly affect a piece's visibility. Releasing high-investment content when the engagement pool is recovering from a viral peak analogous to scheduling a premiere after a blockbuster season may yield superior audience capture. Second, the model suggests that maintaining a steady volume of keyword-rich, multimedia-supported articles sustains the low-engagement base that feeds future viral cycles, rather than concentrating all resources on infrequent high-stakes releases. Third, platform curators may use cycle phase detection monitoring aggregate sharing patterns over time to anticipate upcoming engagement troughs and schedule promotional pushes accordingly.

These principles are consistent with findings from the brand social media literature, where strategic content diversity and timing have been shown to correlate with sustained audience engagement (Liu et al., 2021), and with ecological perspectives on information diffusion that emphasise the role of background content in enabling viral spread (Mapunda et al., 2018).

4. CONCLUSION

This study demonstrates that the Lotka-Volterra predator-prey model provides an effective and theoretically grounded framework for analysing audience engagement dynamics on digital media platforms. By parameterising the model using article-level features from the Mashable Online News Popularity dataset, we showed that the competition between high-engagement and low-engagement content generates the same type of oscillatory cycles predicted by classical ecological theory. Stability analysis confirmed that the interior equilibrium representing coexistence of both content types exhibits neutral stability, meaning the system perpetually cycles rather than converging to a fixed state or collapsing.

For practitioners in digital media, audio-visual production, and content strategy, these findings suggest that engagement is not a static property of individual content items but an emergent, cyclical phenomenon shaped by competitive interactions across the content ecosystem. Understanding where the system sits in its engagement cycle whether the audience pool is saturated with viral content or currently underserved can meaningfully inform release scheduling, content investment, and platform curation decisions.

Future research should incorporate temporal trend effects such as seasonal publishing patterns and breaking news events, extend the framework to multi-platform environments where engagement dynamics differ by medium, and explore nonlinear generalisations of the model such as logistic growth terms to better capture viral saturation effects.

Integrating real-time data streams and reinforcement learning approaches could also enable dynamic parameter adaptation, moving from descriptive to predictive modelling of content engagement cycles.

CONFLICT OF INTERESTS

None.

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