

NUMERICAL MODELING OF THE IMPACT OF ONLINE REVIEWS AND NEGATIVE INFORMATION ON TOURIST VISIT INTENTION

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ABSTRACT. This article develops a nonlinear dynamic model for assessing the joint effect of online reviews, ratings, communication activity, and negative information on tourist visit intention. The model contains five dimensionless state indices: destination image, visit intention, communication influence, online-rating influence, and negative-information pressure. Numerical solutions are obtained using the classical fourth-order Runge–Kutta method. Five scenarios are compared over sixty conditional time units: baseline, stronger communication, improved online ratings, growth of negative information, and integrated management. Using a single consistent parameter set, the final visit-intention index increases by about 19.5% under stronger communication, by 33.8% when the rating channel improves, and by 58.3% under integrated management, whereas stronger negative information reduces it by about 23.0%. The results support the use of the model as a scenario-analysis tool for digital destination-image management.

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Key words: online reviews; eWOM; destination image; tourist visit intention; negative information; nonlinear dynamic model; Runge–Kutta method; scenario analysis.

Introduction

The digital information environment has fundamentally transformed the way tourists choose destinations. Before planning a trip, users form perceptions of a destination through search engines, social networks, booking platforms, and reviews on map services. Consequently, tourism attractiveness is now determined not only by natural and cultural resources or service infrastructure, but also by destination image, ratings, and reputational signals in the digital environment. Uzbekistan's tourism policy likewise identifies the active promotion of national tourism products in international markets, targeted advertising, and the use of modern marketing tools as priority tasks [1]. Under these conditions, quantitatively assessing the impact of online information flows on visit intention can strengthen the scientific basis of managerial decision-making.

Destination image is a multifactorial and time-varying system. Positive reviews and high ratings may increase trust in a destination and raise the likelihood of a visit, whereas negative reviews, complaints about service quality, and unfavorable information concerning safety or prices may have the opposite effect. In addition, a communication campaign may simultaneously affect destination image, review activity, and the spread of negative information. Therefore, the relationships among these variables should be examined not only through static regression coefficients but also through a dynamic system that explicitly accounts for time.

The purpose of this study is to represent the impact of online reviews and negative information on tourist visit intention using a system of nonlinear differential equations, solve the model numerically by the fourth-order Runge–Kutta method, and compare the outcomes of different management scenarios. The practical

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objectives are to formalize the influence mechanisms among the main digital and reputational factors, provide a reproducible computational algorithm based on a single parameter set, and evaluate how management measures targeting communication, ratings, and negative information affect final visit intention. Until the model is calibrated using observed data for a real destination, it should be interpreted not as a forecasting instrument but as a conceptual and numerical platform for scenario and sensitivity analysis.

Literature review and positioning of the study

Classical studies of destination image distinguish its functional and psychological components as well as holistic and individual attributes [2]. Baloglu and McCleary linked destination-image formation to information sources and personal factors [3], while Beerli and Martin systematized the interacting roles of information sources, previous experience, and tourist characteristics [4]. These approaches provide a theoretical basis for introducing digital information sources into the model as an independent driver of image dynamics.

The Internet has sharply increased the influence of electronic word of mouth (eWOM) in the tourism market. Litvin, Goldsmith, and Pan showed that online opinion exchange significantly affects consumer decisions in hospitality and tourism [5]. Xiang and Gretzel demonstrated that social media has become an important source in the travel-information search process [6]. Jalilvand et al. empirically examined the structural relationships among eWOM, destination image, tourist attitude toward destination and travel intention, documenting both a direct effect of eWOM on visit intention and an indirect effect mediated by destination image [7].

Subsequent research has confirmed the robustness of these relationships using broader empirical evidence. In a meta-analysis of 87 studies, Afshardoost and Eshaghi showed that destination image significantly predicts tourists' behavioral intentions [8]. Setiawan et al. analyzed the mediating roles of destination image, trust, and satisfaction in the effect of eWOM on visit intention [9]. Guo and Pesonen showed that the rating and content of online travel reviews can affect tourists' cognitive, affective, and conative image components differently; in particular, low-rated negative reviews may cause substantial damage to affective destination image [10].

Reputational risk and negative information also constitute independent determinants of behavioral intentions. Siyamiyan Gorji, Almeida Garcia, and Mercade-Mele found that risk- and crisis-related information can weaken destination image and subsequent behavioral intentions [11]. Ko, combining large-scale online-review and survey data, showed that destination image is associated with the perceived usefulness and reception of reviews [12]. Thus, although the empirical literature has extensively examined the relationships among eWOM, image, ratings, and visit intention, scenario-based analysis of feedback links and saturation mechanisms among these factors within a single nonlinear dynamic system remains relatively uncommon. The present study addresses this gap at the conceptual and numerical level.

Model and numerical strategy

The study is based on a deductive modeling approach. Five state indicators of the tourist decision process are selected and their interactions are represented by differential equations in the form of positive and negative flows. The variables are interpreted as dimensionless indices of relative intensity and are not restricted to the interval $[0, 1]$. This interpretation preserves the possibility of calibrating the model using different data sources.

Table 1. Model variables

Symbol	Meaning	Interpretation
$I(t)$	Destination image	Intensity of the overall positive perception of the destination
$B(t)$	Visit intention	Relative index of propensity to visit or book
$C(t)$	Communication influence	Flow of advertising, media activity, and positive content
$R(t)$	Online-rating influence	Positive reputational signal from reviews and ratings
$N(t)$	Negative-information pressure	Intensity of negative reviews and reputational risk

Source: Authors' calculations.

The following nonlinear system is adopted for the state variables:

$$\begin{aligned}\frac{dI}{dt} &= u_I + a_1C + a_2R - a_3NI - a_4I - \mu_1I^2, \\ \frac{dB}{dt} &= b_1I + b_2R - b_3NB - b_4B - \mu_2B^2, \\ \frac{dC}{dt} &= u_C + c_1B - c_2C - \mu_3C^2, \\ \frac{dR}{dt} &= u_R + r_1B + r_2I - r_3R - \mu_4R^2, \\ \frac{dN}{dt} &= d_1B - d_2CN - d_3N - \mu_5N^2.\end{aligned}$$

Here, all coefficients a_i , b_i , c_i , r_i , d_i , and μ_i are positive, while u_I , u_C , and u_R are nonnegative parameters representing source inflows. In the first equation, communication and ratings increase destination image, whereas negative information damages image through the product NI . The second equation represents the positive response of visit intention to destination image and ratings and its negative response to adverse information. The quadratic terms $-\mu_iX^2$ act as internal saturation mechanisms that prevent unbounded growth. The term $-d_2CN$ in the $N(t)$ equation represents the possibility that active communication can mitigate negative-information pressure.

For the numerical experiment, the initial conditions are

$$I(0) = 0.40, \quad B(0) = 0.30, \quad C(0) = 0.35, \quad R(0) = 0.32, \quad N(0) = 0.25.$$

The computational horizon is $T = 60$ conditional time units with step size $h = 0.1$. The baseline parameters are

$$\begin{aligned}u_I &= 0.02, & u_C &= 0.03, & u_R &= 0.02, \\ a_1 &= 0.15, & a_2 &= 0.12, & a_3 &= 0.06, & a_4 &= 0.10, & \mu_1 &= 0.02, \\ b_1 &= 0.13, & b_2 &= 0.10, & b_3 &= 0.05, & b_4 &= 0.09, & \mu_2 &= 0.018, \\ c_1 &= 0.11, & c_2 &= 0.12, & \mu_3 &= 0.015, \\ r_1 &= 0.08, & r_2 &= 0.09, & r_3 &= 0.11, & \mu_4 &= 0.014, \\ d_1 &= 0.06, & d_2 &= 0.07, & d_3 &= 0.10, & \mu_5 &= 0.016.\end{aligned}$$

Because a closed-form analytical solution is generally unavailable, the classical fourth-order Runge–Kutta scheme is applied [13,14,15]. Let

$$X(t) = (I(t), B(t), C(t), R(t), N(t))^T, \quad \frac{dX}{dt} = F(X).$$

At each step,

$$\begin{aligned}K_1 &= F(X_n), \\ K_2 &= F\left(X_n + \frac{h}{2}K_1\right), \\ K_3 &= F\left(X_n + \frac{h}{2}K_2\right), \\ K_4 &= F(X_n + hK_3), \\ X_{n+1} &= X_n + \frac{h}{6}(K_1 + 2K_2 + 2K_3 + K_4).\end{aligned}$$

All scenarios are computed from the same initial state and with the same values of T and h . The parameter modifications are summarized in Table 2.

Table 2. Parameter changes across scenarios

Scenario	Modification
Baseline	All parameters at baseline values
Communication +30%	u_C, a_1, c_1 multiplied by 1.30
Rating +25%	a_2, b_2, r_1, r_2 multiplied by 1.25
Negative information +40%	a_3, b_3, d_1 multiplied by 1.40
Integrated management	Communication +30%; rating +25%; d_2 multiplied by 1.30

Source: Authors' calculations.

Verification of the first RK4 step.

To demonstrate computational reproducibility, the first step of the baseline scenario, from $t_0 = 0$ to $t_1 = 0.1$, is presented numerically. The initial vector is

$$X_0 = (0.40, 0.30, 0.35, 0.32, 0.25).$$

The four RK4 increments are

$$\begin{aligned} K_1 &= (0.061700, 0.051630, 0.019163, 0.043366, -0.014125), \\ K_2 &= (0.061717, 0.051966, 0.019321, 0.043593, -0.013893), \\ K_3 &= (0.061719, 0.051965, 0.019322, 0.043593, -0.013894), \\ K_4 &= (0.061738, 0.052300, 0.019482, 0.043819, -0.013663). \end{aligned}$$

Therefore,

$$X_1 = X_0 + \frac{0.1}{6}(K_1 + 2K_2 + 2K_3 + K_4) = (0.406172, 0.305197, 0.351932, 0.324359, 0.248611).$$

Thus, after the first step,

$$\begin{aligned} I(0.1) &= 0.406172, & B(0.1) &= 0.305197, & C(0.1) &= 0.351932, \\ R(0.1) &= 0.324359, & N(0.1) &= 0.248611. \end{aligned}$$

The remaining 599 steps are carried out using exactly the same algorithm.

Results

Table 3 presents the final values obtained at $T = 60$ from the same RK4 algorithm and a consistent parameter set for all scenarios.

Table 3. Final scenario results at $T = 60$

Scenario	$I(60)$	$B(60)$	$C(60)$	$R(60)$	$N(60)$
Baseline	4.300	4.616	3.155	4.434	0.827
Communication +30%	5.731	5.518	4.404	5.264	0.786
Rating +25%	5.739	6.179	3.929	6.389	0.949
Negative information +40%	3.357	3.554	2.598	3.685	0.999
Integrated management	7.429	7.306	5.376	7.398	0.729

Source: Authors' calculations.

In the baseline scenario, visit intention reaches $B(60) = 4.616$. When the communication channel is strengthened, $B(60) = 5.518$, representing a 19.5% increase relative to the baseline. When the influence of online ratings is strengthened, $B(60) = 6.179$, corresponding to a 33.8% increase. This result indicates that the rating signal affects visit intention directly through the term b_2R and indirectly through mutual reinforcement between destination image and ratings. When the negative-information parameters are increased by 40%, $B(60)$ falls to 3.554, which is 23.0% below the baseline. Integrated management produces the largest effect: $B(60) = 7.306$, or 58.3% above the baseline level.

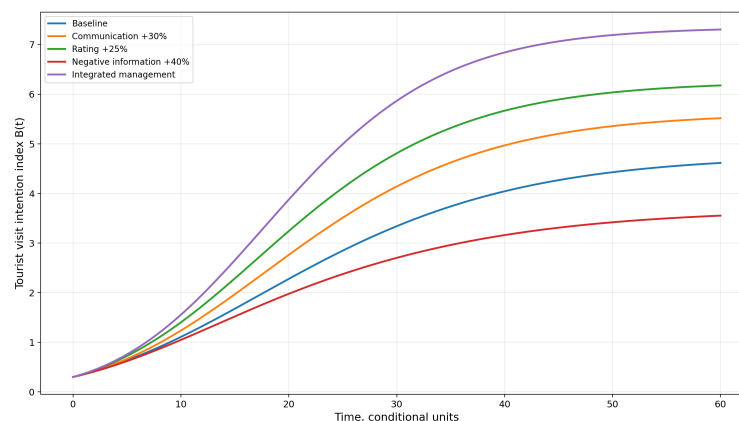


Figure 1. Dynamics of tourist visit intention $B(t)$ under different scenarios

Source: Authors' calculations.

Figure 1 shows how differences among the scenarios develop over time. Initially, all trajectories start from the same point, but when positive reputational channels are strengthened, the gap increases cumulatively. Under the negative-information scenario, the growth rate begins to slow at an early stage. The advantage of integrated management is explained not by a change in a single coefficient, but by the simultaneous strengthening of feedback links among communication, destination image, and ratings.

An important trade-off is observed in the dynamics of negative information. Strengthening only the rating channel increases visit intention and activity, but the rise in $B(t)$ creates additional pressure on $N(t)$ through the term $d_1 B$. As a result, under the rating scenario $N(60) = 0.949$, which is 14.8% above the baseline. Direct strengthening of the negative-information parameters leads to $N(60) = 0.999$. Under integrated management, however, the increase in d_2 strengthens the channel through which communication mitigates negative information and reduces $N(60)$ to 0.729, which is 11.8% below the baseline level.

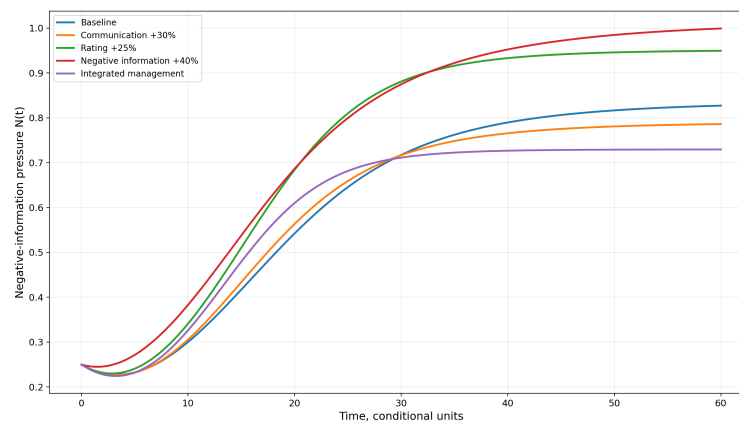


Figure 2. Dynamics of negative-information pressure $N(t)$ under different scenarios

Source: Authors' calculations.

Discussion and practical implications

From a managerial perspective, the results yield three conclusions. First, improving online ratings and destination image increases visit intention, but stimulating demand alone does not automatically reduce reputational risk. Second, a mitigation mechanism—such as responding to negative reviews, correcting service deficiencies, and maintaining active communication—is required as an independent management channel. Third, the highest visit intention is achieved under multichannel management. Therefore, tourism organizations should monitor not only advertising and rating indicators, but also review valence, response speed, complaint topics, and reputational-risk indicators within a unified system.

The model also highlights the distinction between demand stimulation and reputational stabilization. The rating scenario strongly increases $B(t)$, but it also produces a higher value of $N(60)$ than the baseline. By contrast, integrated management combines communication, stronger rating effects, and an explicit negative-information mitigation mechanism. This produces the highest final destination image and visit intention while keeping negative-information pressure relatively low.

The current coefficients are hypothetical and have not been estimated using observational data for a specific destination. Therefore, the numerical values do not represent actual tourist numbers or exact probabilities; rather, they show relative dynamics across scenarios. At the next stage, the coefficients can be calibrated using Google Reviews, TripAdvisor, Booking.com, social-media posts, search trends, booking data, and visit statistics. Parameter-estimation methods such as nonlinear least squares, Bayesian calibration, or state-space approaches could transform the model into a forecasting tool.

Additional graphical results

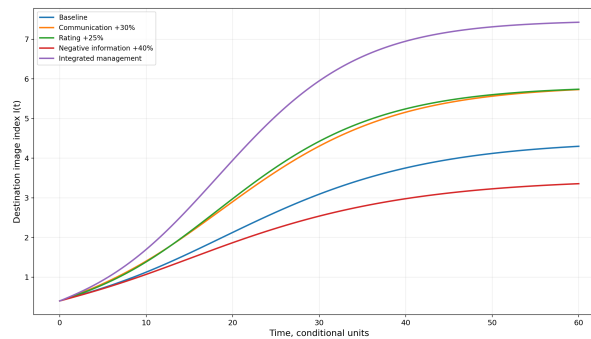


Figure 3. Dynamics of destination image $I(t)$ under different scenarios

Source: Authors' calculations.

Figure 3 shows that strengthening the communication and rating channels shifts the destination-image trajectory above the baseline, whereas stronger negative information substantially constrains the growth of $I(t)$. Under integrated management, the combined effect of the positive channels produces the highest final destination-image index.

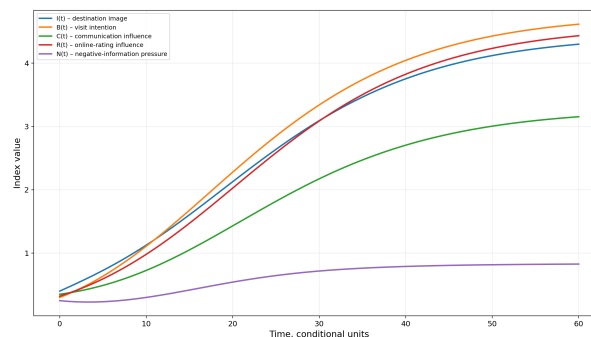


Figure 4. Dynamics of $I(t)$, $B(t)$, $C(t)$, $R(t)$, and $N(t)$ in the baseline scenario

Source: Authors' calculations.

Figure 4 illustrates the simultaneous evolution of the five state variables in the baseline scenario. $I(t)$, $B(t)$, $C(t)$, and $R(t)$ initially increase more rapidly and then slow under the effect of the quadratic saturation terms, whereas $N(t)$ stabilizes at a lower level.

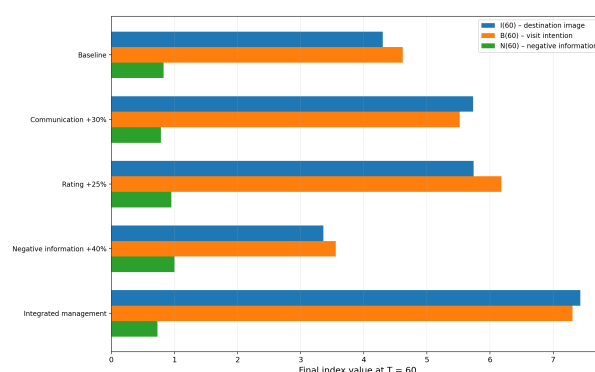


Figure 5. Comparison of final $I(60)$, $B(60)$, and $N(60)$ values across scenarios at $T = 60$

Source: Authors' calculations.

Figure 5 compares the final states in a single graph. Integrated management yields the highest values of $I(60)$ and $B(60)$ and one of the lowest values of $N(60)$. This result indicates that positive communication, online ratings, and measures to mitigate negative information are more effective when applied jointly rather than separately.

Conclusion

This study developed a five-variable nonlinear dynamic model describing the interactions among online reviews, ratings, communication influence, negative information, and tourist visit intention. A unified parameter set and the fourth-order Runge–Kutta method were used to ensure consistent and reproducible scenario calculations.

In the numerical experiment, stronger communication increased final visit intention by 19.5%, improvement of the rating channel by 33.8%, and integrated management by 58.3%. Stronger negative information reduced visit intention by 23.0%. At the same time, increasing ratings alone was found not to eliminate negative-information pressure completely. The most favorable outcome was observed under the integrated scenario, which actively manages the mitigation of negative information while simultaneously strengthening positive communication and ratings.

From a practical perspective, four directions are recommended for destination management: continuous monitoring of online ratings and reviews; rapid and substantive responses to negative reviews; coordination of positive media and social-media communication with service quality; and integration of digital reputation indicators with actual visit and booking data. Future research should calibrate the model using real data for a specific tourist destination in Uzbekistan, analyze parameter sensitivity and the stability of equilibrium states, and introduce seasonality and external shocks as separate variables.

REFERENCES

1. Resolution of the President of the Republic of Uzbekistan “On measures to organize the activities of the Tourism Committee of the Republic of Uzbekistan and accelerate the development of the tourism sector.” 20 November 2025. president.uz. [in Uzbek].
2. Echtner C. M., Ritchie J. R. B. The meaning and measurement of destination image // Journal of Tourism Studies. 1991. Vol. 2, No. 2. P. 2–12.
3. Baloglu S., McCleary K. W. A model of destination image formation // Annals of Tourism Research. 1999. Vol. 26, No. 4. P. 868–897. DOI: 10.1016/S0160-7383(99)00030-4.
4. Beerli A., Martin J. D. Factors influencing destination image // Annals of Tourism Research. 2004. Vol. 31, No. 3. P. 657–681. DOI: 10.1016/j.annals.2004.01.010.
5. Litvin S. W., Goldsmith R. E., Pan B. Electronic word-of-mouth in hospitality and tourism management // Tourism Management. 2008. Vol. 29, No. 3. P. 458–468. DOI: 10.1016/j.tourman.2007.05.011.

6. Xiang Z., Gretzel U. Role of social media in online travel information search // *Tourism Management*. 2010. Vol. 31, No. 2. P. 179–188. DOI: 10.1016/j.tourman.2009.02.016.
7. Jalilvand M.R., Samiei N., Dini B., Manzari P.Y. Examining the structural relationships of electronic word of mouth, destination image, tourist attitude toward destination and travel intention: An integrated approach // *Journal of Destination Marketing & Management*. 2012. Vol. 1, No. 1–2. P. 134–143. DOI: 10.1016/j.jdmm.2012.10.001.
8. Afshardoost M., Eshaghi M.S. Destination image and tourist behavioural intentions: A meta-analysis // *Tourism Management*. 2020. Vol. 81. 104154. DOI: 10.1016/j.tourman.2020.104154.
9. Setiawan P.Y., Troena E.A., Armanu, Noermijati. How electronic word of mouth (e-WOM) triggers intention to visit through destination image, trust and satisfaction: the perception of a potential tourist in Japan and Indonesia // *Online Information Review*. 2021. Vol. 45, No. 5. P. 861–878. DOI: 10.1108/OIR-03-2019-0111.
10. Guo X., Pesonen J.A. The role of online travel reviews in evolving tourists' perceived destination image // *Scandinavian Journal of Hospitality and Tourism*. 2022. Vol. 22, No. 4–5. P. 372–392. DOI: 10.1080/15022250.2022.2112414.
11. Siyamiyan Gorji A., Almeida Garcia F., Mercade-Mele P. Tourists' perceived destination image and behavioral intentions towards a sanctioned destination: Comparing visitors and non-visitors // *Tourism Management Perspectives*. 2023. Vol. 45. 101062. DOI: 10.1016/j.tmp.2022.101062.
12. Ko E.E. Impact of tourism destination image on perceived usefulness of online reviews: Psychological distance effect and two methodologies // *International Journal of Tourism Research*. 2024. DOI: 10.1002/jtr.2690.
13. Perko L. *Differential Equations and Dynamical Systems*. 3rd ed. New York: Springer, 2001. 553 p.
14. Butcher J.C. *Numerical Methods for Ordinary Differential Equations*. 3rd ed. Chichester: Wiley, 2016. 544 p.
15. Hairer E., Nørsett S.P., Wanner G. *Solving Ordinary Differential Equations I: Nonstiff Problems*. 2nd ed. Berlin: Springer, 1993. 528 p.

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