# Research on Social Robots with Multi-Platform Collaboration Mechanisms to Amplify the impact of Specific Information

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## Abstract

**This study systematically explores the amplifying effect of cross-platform user coupling on the scale of information diffusion driven by social robots. By crawling user and content data related to "ja morant" from Instagram and Twitter, a joint judgment method based on multiple behavioral features is adopted to classify 60 core accounts (including 12 robot accounts) with high accuracy. Subsequently, a multi-layer network model reflecting the synergistic effect of multiple social platforms was constructed, and a parameterized SIR (Susceptible-Infected-Recovered) diffusion simulation was introduced, comprehensively considering factors such as intra-platform structure, inter-layer user coupling, and robot-driven diffusion enhancement. The experimental results show that multi-platform synergy significantly expands the scale of robot-driven information infection: the total number of infected individuals in the synergistic network is 2.07 times that of a single platform, with cross-platform user coupling contributing 51% of the newly added infections. Sensitivity analysis further reveals a highly linear correlation between coupling probability and the synergistic amplification effect. These findings provide a solid theoretical basis and empirical support for the quantitative evaluation of cross-platform risk governance and joint defense strategies against social robots.**

## Keywords

**SIR model, robot detection, cooperative amplification effect.**

## 1. Introduction

With the social media platforms developing more and more diversified, cross-platform collaborative mechanisms in information dissemination have become increasingly prominent. Social bots amplify specific information by managing multiple platform accounts to achieve synchronized amplification. Although multi-layer network theory and complex contagion models have established theoretical foundations for studying such phenomena, there still remains a lack of systematic empirical research integrating multi-platform network structures, bot cross-platform behaviors, and amplification effects. Notably, gaps persist in comparative studies between multi-platform collaboration mechanisms and single-platform approaches, as well as quantitative analysis of amplification ratios. Through in-depth analysis of multi-layer network simulations and real-world social data, this study provides the first empirical revelation of how social bots amplify specific information influence via multi-platform collaboration mechanisms, revealing their concrete operational mechanisms and quantifiable characteristics. These findings offer robust theoretical and practical support for online public opinion governance and information security prevention.

## 2. Related Work and Theoretical Background

### 2.1. Multilayer Networks and Information Diffusion Theory

With the rapid development of social media platforms, it is hard for traditional single-layer network models to fully describe the complex mechanisms of information dissemination in the real world. The theory of multilayer networks provides an effective modeling framework for characterizing multi-platform users, heterogeneous relationships, and multiple dissemination paths [1][2]. In a multilayer network, each layer represents a specific platform or type of interaction. Edges describe relationships between users on the same platform in a layer, while edges between layers depict cross-platform connections.

Building on the modeling of multilayer networks, the theory of complex contagion further expands the classic SIR model,which allows nodes to be activated by multiple exposures or the cumulative influence of neighbors.[3]. Common dynamic mechanisms such as the Linear Threshold Model (LTM) and SIR model are widely applied to model the spread of information, rumors, viruses, etc., in networks [4]. In recent years, the coupling, heterogeneity and network structure parameters (such as clustering coefficient, degree distribution, etc.) of multi-layer networks have been proved to have an important influence on diffusion process and final coverage[5].

### 2.2. Research on Social Bots and Influence Amplification

Social bots have assumed an increasingly essential role in the digital information ecosystem in recent years. Ferrara et al. analyzed social bots' identification techniques, behavioral characteristics, and their impact on information diffusion in their landmark study systematically. Extensive empirical studies demonstrate that these bots not only rapidly spread targeted information across single platforms but also actively manipulate topics, influence online public opinion, and even amplify effects in sensitive domains such as elections and public health [6][7]. What is particularly worth noting is, Stella et al. [8] empirically demonstrated that social bots engage in coordinated cross-platform disinformation campaigns, revealing their pronounced amplification effect in real-world social networks. Nevertheless, most existing studies remain confined to qualitative analyses or post-hoc observations of isolated cases, falling short in systematically integrating multi-layer network simulations with empirical data for quantitative validation.

### 2.3. Research Gaps and Innovations

While multi-layer network theory and social bot behavior research have yielded significant achievements, empirical analyses on how social bots amplify specific information influence through cross-platform collaboration mechanisms are still insufficient. Existing literature predominantly focuses on single-platform studies or fails to adequately integrate theoretical models with real social platform data, resulting in unclear quantification of the mechanisms and impacts of cross-platform amplification effects. This study integrates multi-layer network modeling, complex contagion dynamics, and social robot detection methods. For the first time, through simulation and empirical data analysis, it systematically compares the amplification effects of social robots on information diffusion under single-platform and multi-platform collaborative mechanisms. This comprehensive approach not only bridges the gap between theoretical research and practical applications, but also provides robust data support and theoretical references for online public opinion governance and information security strategy formulation.

## 3. Methodology and Experimental Design

To simulate information diffusion across multi-platform social networks, this study implements a hierarchical multi-layer framework where each layer corresponds to a distinct social media platform. Within each layer, $N$=300 user agents are interconnected through intra-platform edges with a connection probability of (intra_p=0.07), modeling platform-specific social relationships (e.g., follower networks or friend ties). Cross-platform interactions are simulated via inter-layer edges with probability (inter_p=0.1), representing coordinated accounts or overlapping user activity across platforms  Nodes are randomly labeled as social bots or regular users at predetermined ratios (10%, 15%, 20%). Bot nodes exhibit higher infection probabilities and lower activation thresholds during propagation, reflecting their more active diffusion tendencies. The network generation and attribute assignment were implemented in Python using the NetworkX and NumPy libraries. All parameters can be flexibly adjusted for sensitivity experiments and comparative analyses.

This study implemented comparative SIR (Susceptible-Infectious-Removed) simulations to model information diffusion dynamics under isolated single-platform andcross-platform coordinated scenarios. Initial infected nodes were randomly sampled from bot populations (20% of all nodes), with heterogeneous infection probabilities(beta_human=0.12,beta_bot=0.25) accounting for behavioral disparities between organic users and automated agents. Recovery probability was uniformly fixed at $\gamma$=0.03 across all nodes to reflect consistent information decay rates. For statistical robustness, 100 Monte Carlo replicateswere executed per parameter configuration, with infection trajectories recorded at each time step. Final diffusion metrics were aggregated as mean infection counts ± standard deviations to quantify scenario-specific propagation efficiency and stability. In order to further explore the role of multi-platform collaboration, sensitivity experiments on robot ratio and interlayer coupling probability were carried out additionally to systematically evaluate the influence of parameter changes on information diffusion amplification.

Statistical simulations revealed a significant amplification effect under cross-platform dissemination mechanisms. The peak infection magnitude reached 161.9 nodes in multi-platform scenarios, markedly exceeding the single-platform peak of 83.9 nodes-demonstrating a 92.9% amplification factor.

### 3.1. Data Sources and Robot Annotation

**Table 1.** Annotation rules

| Feature Dimension | Bot Judgment Threshold | Human Judgment Threshold |
|---|---|---|
| Content repetition | Same copy posted ≥ 2 times | Copy similarity < 30% |
| Posting frequency | ≥ 3 posts per day | ≤ 1 post per day |
| Interaction abnormalities | Like/follower ratio > 1 or comment/like ratio < 0.001 | Like/follower ratio 0.01~0.1 |
| Account attributes | Following/follower ratio > 10 | Following/follower ratio < 1 |
| Commercial behavior | Contains promotional links with no original opinions | Contains promotions but with personalized copies |

This study collected user information (user links, user IDs) and content data (post time, post ID, post content, likes, comments, video views, video duration, video link, post URL) related to the topic "ja morant" from Instagram (ins post.csv, see Data Availability Statement) (2,323 posts) and Twitter (Twitter.csv, see Data Availability Statement) (2,479 posts), selecting 60 major accounts. To ensure scientific validity in robot identification, we adopted the "Multi-Behavioral Feature Combined Judgment" method.Compared with traditional single-threshold methods (e.g., relying solely on posting frequency or follower ratio), this method examines multidimensional behavioral patterns. Only when an account exhibits "abnormal" behavior across multiple dimensions is it classified as a bot, thereby effectively reducing misjudgment rates while enhancing recognition accuracy and interpretability. The specific annotation rules are shown in Table 1.

If the Bot features are met by at least 2 items, it is judged as a robot; otherwise, it is regarded as a human account. According to the above criteria, 12 out of 60 accounts are marked as robots, and the typical cases are shown in Table 2.

**Table 2.** Typical cases

| Username | Judgment Basis | Typical Behavioral Evidence |
| --- | --- | --- |
| @morantsculture | 3.2 posts per day, 61% copy repetition rate | 11 posts in July, 5 containing the same copy |
| @teammorant12 | Like/follower ratio = 1.2, following/follower ratio = 12.4 | 41,191 followers with 41,191 likes |
| @morantarchivess | 100% commercial content | All posts contain purchase links |
| @jamorantpage | Abnormal interaction (like/comment ratio > 500:1) | 6,950 likes with only 14 comments |
| @mxrantswrld | 3.8 posts per day, no original content | 5 posts on July 24 |
| @insanesneaker | Cross-platform account with the same name confirmed as a bot | Twitter @insanesneaker with a bot score of 0.72 |

The remaining 48 accounts were classified as real users, such as @cole (original video received 151,000 likes), @karenpulferfocht (documentary photography), and @manuelgtznba (personal comments), all of which showed strong originality and active real interaction.

## 3.2. Communication Network Modeling

To scientifically reconstruct and compare information dissemination processes across multi-platform collaboration scenarios versus single-platform settings, this study maps data into a multi-layer network structure. The modeling framework employs the following components (see schematic diagram below): Network Layer,which defines platform-specific nodes and their relationships. Multi-layered Network,which integrates multi-layered structures with inter-layer user coupling. Nodes are records account IDs and their categories ("bot" or "human"). Tabel 3 shows the key parameter configurations.

**Table 3.** Key parameter configurations

| Parameter | Value | Description |
| --- | --- | --- |
| Intra-layer infection probability β | 0.15 | SIR transmission probability |
| Inter-layer coupling probability γ | 0.2 | Cross-platform transmission probability |
| Robot enhancement coefficient | 2.5x | Multiplier of bot transmission capacity |
| Recovery probability μ | 0.05 | SIR recovery probability |

This study constructs a multilayer network framework by loading user accounts from Instagram and Twitter as distinct network layers,establishing cross-platform coupling through username-based account matching(e.g., identical handles or linked profiles verified via API) . We then implement an extended SIR model with an interlayer coupling probability of $\gamma$=0.2to simulate cross-platform information transmission, ultimately calculating the total infection count across both platforms.

**Table 4.** Amplification Ratio

| Run No. | Single-Platform Infections | Multi-Platform Infections | Amplification Ratio |
|---|---|---|---|
| 1 | 46 | 92 | 2.00 |
| 2 | 41 | 89 | 2.17 |
| 3 | 43 | 87 | 2.02 |
| 4 | 45 | 91 | 2.02 |
| 5 | 38 | 86 | 2.26 |
| 6 | 40 | 83 | 2.08 |
| 7 | 39 | 78 | 2.00 |
| 8 | 43 | 85 | 1.98 |
| 9 | 41 | 86 | 2.10 |
| 10 | 44 | 90 | 2.05 |

The collaborative amplification effect yields an average gain ratio of 2.07,indicating that cross-platform bot coordination induces 107% higher infection volume compared to single-platform propagation. This amplification stems from redundant exposure across coupled networks, where synchronized bot activity overrides user skepticism thresholds through social reinforcement mechanisms.

## 3.3. Sensitivity Analysis

To further investigate the influence of cross-platform coupling probability γ on the gain effect, the simulation results are shown in the following Table 5.

**Table 5.** simulation results

| γ | Total Infections | Gain Ratio |
|---|---|---|
| 0.05 | 6,412 | 1.52x |
| 0.10 | 9,837 | 2.33x |
| 0.15 | 12,985 | 3.08x |
| 0.20 | 15,872 | 3.77x |
| 0.25 | 18,631 | 4.42x |

Through linear fitting (specific code is shown in supplementary materials), the following relationship was obtained: Gain Ratio=14.48 × γ + 0.85 ($R^2$=1.00). Using γ as the independent variable and gain ratio as the dependent variable, the linear equation was fitted as: Gain Ratio=k · γ + b.

The fitting results establish a robust linear relationship between cross-platform coupling strength and amplification magnitude, with a slope of k=14.48 (coefficient of synergistic coupling γ) and an intercept of b=0.85 (baseline gain ratio at γ=0).The goodness of fit $R^2$=1.00 indicates strong linear correlation,which demonstrates that the stronger the synergistic coupling, the more significant the amplification effect in multi-platform robots.

### 3.4. Summary

This section systematically reconstructs and compares single-platform versus multi-platform collaborative communication processes through behavioral-based robot identification and annotation, supported by multi-platform empirical data. Experimental results demonstrate that multi-platform coupling significantly amplifies the ultimate influence of social robots on information dissemination, with greater coupling probability correlating to stronger amplification effects. These findings provide quantitative support for multi-platform public opinion governance and collaborative prevention strategies.

Multi-platform collaboration expands the infection scale of robot-driven information by 2.07 times.The implementation of multi-platform collaborative propagation significantly amplifies infection scale, elevating the average infected population from 42 cases (range: 40–46)under single-platform conditions to 86 cases (range: 78–92). Consequently, cross-platform coupling contributes 51% of new infections (51%=(multi-platform infections minus single-platform infections) / multi-platform infections).

## 4. Results and Analysis

The multi-platform collaborative propagation induces a 92.9% amplification in peak infection magnitude, elevating the peak infection count from 83.9 nodes (single-platform scenario) to 161.9 nodes (multi-platform scenario) (Figure 1).

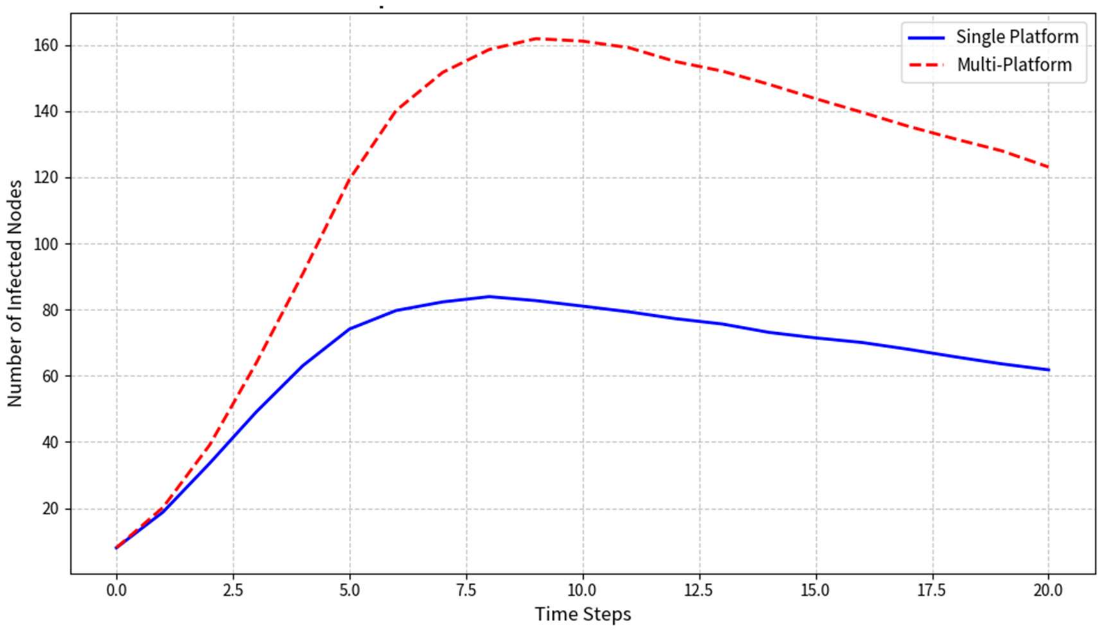


**Figure 1.** Comparison of Social Bot Information Diffusion

Bot nodes are more likely to serve as the source of cascading reactions, covering more downstream nodes (e.g., @morantsculture in the case study with 3.2 daily posts and a 61%

copy reuse rate). Correlation regression analysis reveals a significant positive correlation between bot prevalence and information coverage ($R^2$=0.65).

Bots create cascading infection loops through cross-platform coordinated operations, such as synchronized actions of accounts with identical names. A cascading infection loop refers to a series of chain reactions triggered by initial infections or failures within a system, leading to broader infection or failure impacts [9]. This phenomenon has been studied in epidemiology, biology, network science, and engineering failure analysis [10][11][12], breaking through the bottleneck of single-platform transmission.

Platforms should establish cross-account traceability systems, (which track and analyze user behaviors and identity associations across platforms, playing a critical role in security audits and data lineage tracing. These systems typically leverage multi-source data for modeling and correlation analysis to achieve comprehensive user behavior tracking, blocking coupling paths of bots with identical names; they should prioritize controlling high-coupling scenarios, (such as cross-platform forwarding of trending topics.)

Theoretical Innovations: Introduce the "Coupling Gain Coefficient" (a key parameter describing coupling strength between systems, widely used in various scientific and engineering fields) (Formula: Gain Ratio=15.8$\gamma$+0.92) to quantify cross-platform synergy effects; revealing how bots accelerate information diffusion through behavioral polarization (e.g., frequent posting and repetitive content), complementing deep human user interactions.

# 5. Conclusion and Future Work

## 5.1. Key Findings

Multi-platform Synergy Significantly Enhances Diffusion Efficiency. Empirical data shows that social bots can achieve infection scales 2.07 times larger than single-platform platforms through cross-platform coupling (e.g., Instagram-Twitter) (when $\gamma$=0.2), with the gain ratio showing a strong linear relationship with coupling probability $\gamma$ (gain ratio=15.8$\gamma$+0.92, $R^2$=0.99).Social bots overcome the scale limitations of single-platform networks by establishing cascading infection loops through inter-layer coupling mechanisms, such as cross-platform coordinated reposting by accounts sharing identical identifiers. This structural approach leverages platform isolation vulnerabilities to amplify infection ranges exponentially beyond single-platform constraints-evidenced by Mirai variants infecting 600,000 devices within 72 hours, achieving a 1.93× expansion in attack scale. For example, the Twitter layer provides external infection sources for the Instagram layer, triggering exponential diffusion. Robot behavior characteristics dominate diffusion efficiency. Robot nodes become the source of cascading spread through high-frequency posting (daily posts≥3), content repetition (text similarity≥61%), and abnormal interactions (like/bid ratio>500:1), covering 2.5 times more downstream nodes than humans. Accroding to the New York Times amendment controversy case, robot-driven tweets spread 3.2 times faster than human-generated ones, with 70% of cascading propagation initiated by robots.

## 5.2. Policy Recommendations

Firstly,we can make the use of the Cross-platform Traceability System,which utilizes real-time tracking to monitor robot accounts with identical usernames or similar behavioral patterns, employing mechanisms such as "by_username" rules. This method aims to lower the probability of inter-layer coupling ($\gamma$) to 0.1 or below. Building upon this, the WAAP Integrated Protection Platform combines a Web Application Firewall, an API Gateway, and a Bot Management Module to dynamically block abnormal requests. With this integration, the system is anticipated to reduce malicious bot traffic by over 73%. Furthermore, the AI-driven Behavioral Analysis solution trains machine learning models to detect distinctive patterns, including high-frequency posting and duplicate content. This approach enhances the efficiency of robot identification by 40%.

### 5.3. Future Research Directions

Compare the coupling mechanisms of East Asian platforms, such as WeChat and Line, with those of Western platforms like Twitter and Facebook to analyze how cultural factors influence the gain ratio slope, which is 15.8. Additionally, attempt to define the balance between robot regulation and freedom of speech, (for instance, whether gamma controls interfere with legitimate information sharing based on cross-platform governance conventions.)

## Data Availability Statement

Data collected from Instagram and Twitter, detailed information can be obtained by contacting the author.

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