Analysis of Evolutionary Patterns in Short-Video Content Preferences Based on Audience Behavior Data

Di Wu[1], Yuqing Song[1], Kai Zhang[1], Ziqing Gao[1], Huanhai Ren[2]
[1]School of Design and Art, Shandong Huayu University of Technology, Dezhou 253034, Shandong, China
[2]School of Information Engineering, Shandong Huayu University of Technology, Dezhou 253034, Shandong, China
Corresponding author: Di Wu (e-mail: sdhygxy_wd2026@163.com)

ABSTRACT User preferences on short-video platforms exhibit dynamic evolutionary characteristics that traditional static recommendation models struggle to capture in terms of drift and abrupt shifts. Based on 32 million user behavior records from a leading platform, this study constructs multi-dimensional feature vectors and proposes an LSTM-based preference drift-and-mutation detection model. Through multi-granularity temporal window dynamic modeling of evolutionary trajectories, the detection accuracy reaches 87.3%, representing a 23.6 percentage point improvement over baseline methods. The study further quantifies the driving mechanisms of content features, social events, and algorithmic interventions, and designs a dynamic recommendation mechanism accordingly. A/B testing results show that user dwell time increased by 18.7% and content diversity improved by 31.2%, providing a theoretical basis and technical pathway for precise recommendation and content ecosystem optimization on short-video platforms.

INDEX TERMS short video,preference evolution,LSTM,mutation detection,dynamic recommendation

I. INTRODUCTION

THE user base of short-video platforms has surpassed 1.2 billion, with average daily usage time reaching 118 minutes, making content consumption a core scene in digital life. User preferences exhibit significant dynamic evolutionary characteristics—both gradual drift and abrupt jumps—and traditional static recommendation models struggle to accommodate rapidly changing information needs [1]. Existing research mostly focuses on short-term interest prediction, lacking systematic modeling of long-term evolutionary patterns and insufficient understanding of the triggering mechanisms and driving factors of preference mutations [2-3]. The "filter bubble" phenomenon exacerbated by algorithm-dominated recommendations has intensified content ecosystem imbalances, urgently calling for recommendation optimization solutions built from a dynamic evolutionary perspective [4]. This study collects 32 million user behavior records, proposes an LSTM-based preference drift-and-mutation detection model, identifies heterogeneity patterns in group evolutionary pathways, quantifies the driving effects of content features, social events, and algorithmic interventions, designs a dynamic recommendation mechanism driven by evolutionary patterns, and conducts empirical validation—providing a theoretical basis and technical pathway for precise recommendation and ecosystem governance on short-video platforms.

II. AUDIENCE BEHAVIOR DATA COLLECTION AND FEATURE MODELING

A. MULTI-SOURCE HETEROGENEOUS DATA ACQUISITION AND PREPROCESSING

User behavior data on short-video platforms are characterized by multi-source heterogeneity, covering dimensions such as viewing completion rate, interaction operations, content attributes, and temporal information [5]. The data collection spans user behavior logs from a leading short-video platform between June 2023 and May 2024, comprising 32 million interaction records from 3.2 million active users (see Table 1). Behavioral data include sequences of operations such as video play duration, likes, comments, shares, and collections; content data include structured fields such as video duration, hashtags, creator attributes, and release time. Data collection was conducted under an authorized license, and user identifiers were desensitized to ensure privacy compliance. To address missing values, outliers, and noise during data collection, an anomaly detection method based on statistical distribution was used to exclude non-behavioral errors (e.g., machine-generated logs or transmission errors), while the K-Nearest Neighbor (KNN) imputation algorithm was applied to handle missing data. Crucially, behavioral samples deviating by more than 3 standard deviations were preserved during this stage, as these extreme data points serve as the primary signals for the preference mutation detection model. Temporal data were aggregated at hourly granularity to construct user behavior time series, laying the data foundation for subsequent preference evolution analysis.

TABLE 1. Data Collection Statistics

Data Dimension	Specific Content	Quantity / Scale	Time Span
User Sample	Number of active users	3.2 million	Jun 2023–May 2024
Behavior Records	Total interaction logs	32 million entries	12 months
Behavior Types	Play / Like / Comment / Share / Collect	5 operation types	Full cycle
Content Sample	Number of videos	5.8 million videos	Full cycle
Hashtags	Number of tag categories	1,247 types	Dynamically updated
Creators	Number of accounts	186,000	Full cycle
Data Granularity	Temporal aggregation unit	Hourly	Full cycle
Anomaly Handling	Proportion of excluded samples	2.3%	Preprocessing stage

B. CONSTRUCTION OF MULTI-DIMENSIONAL AUDIENCE BEHAVIOR FEATURE VECTORS

Accurate representation of user preferences relies on the effective extraction and fusion of multi-dimensional features. Based on behavioral data, a feature vector encompassing three dimensions—content preference, interaction intensity, and temporal pattern—is constructed [6]. The content preference dimension generates 128-dimensional semantic embedding vectors via a hashtag co-occurrence matrix and the Word2Vec algorithm to capture users' inclinations toward different content types. The interaction intensity dimension designs a weighted scoring mechanism that assigns different weight coefficients to likes, comments, shares, and collections (1.0, 2.5, 3.2, and 1.8, respectively; these coefficients are set by reference to empirical values from quantitative research on behavioral engagement depth and confirmed through five-fold cross-validation optimization), comprehensively reflecting users' depth of engagement. To quantitatively synthesize the multi-dimensional nature of user engagement, we define an interaction intensity score, S_i, which functions as a proxy for interest depth. This metric is formulated as a linear combination of discrete behavioral signals:

$$S_i = w_1 \cdot N_{\text{like}} + w_2 \cdot N_{\text{comment}} + w_3 \cdot N_{\text{share}} + w_4 \cdot N_{\text{collect}} \tag{1}$$

In this expression, S_i serves as the target variable for user i, while the parameters N_{like}, N_{comment}, N_{share}, and N_{collect} capture the raw counts of specific actions; N_{like}, N_{comment}, N_{share}, and N_{collect} represent the number of likes, comments, shares, and collections, respectively; $w_1 = 1.0$, $w_2 = 2.5$, $w_3 = 3.2$, and $w_4 = 1.8$ are the corresponding weight coefficients, whose magnitudes reflect the representational capacity of each behavior for user engagement depth. The temporal pattern dimension extracts the distribution of active time periods, the rate of change in viewing frequency, and statistical features of behavioral intervals to characterize the time dependence of preference evolution. After Z-score standardization, the feature vectors are input into downstream models to effectively reduce interference from dimensional differences on the analysis results. Experimental validation shows that this feature system achieves a silhouette coefficient of 0.82 in user clustering tasks, outperforming traditional single-dimension feature representation methods.

III. IDENTIFICATION OF TEMPORAL PATTERNS IN CONTENT PREFERENCE EVOLUTION

A. LSTM-BASED PREFERENCE DRIFT AND MUTATION DETECTION

User content preferences exhibit two evolutionary modes in the time dimension—gradual drift and abrupt jumps—and traditional time-series analysis methods struggle to capture both dynamic characteristics simultaneously. This study constructs a preference evolution prediction model based on Long Short-Term Memory (LSTM) networks, learning long-term dependencies in user behavior sequences through gating mechanisms [7]. The model architecture comprises two LSTM layers (with hidden layer dimensions of 256 and 128, determined via Bayesian hyperparameter optimization) and a fully connected output layer; mean squared error is adopted as the loss function and the Adam optimizer is used for parameter updates. Training data are divided into sliding window samples by time series, with the input sequence length set to 14 days to predict the preference vector for the following 7 days. The model's root mean squared error on the validation set is 0.073, a 41.3% reduction compared to the traditional ARIMA model. Preference mutation events are identified by computing the Euclidean distance between predicted and actual values to set a dynamic threshold. The criterion for determining a preference mutation is:

$$D_t = \left\| \mathbf{P}_t^{\text{pred}} - \mathbf{P}_t^{\text{actual}} \right\| > \mu_D + 2\sigma_D \tag{2}$$

where D_t represents the preference prediction deviation distance at time t; $\mathbf{P}_t^{\text{pred}}$ and $\mathbf{P}_t^{\text{actual}}$ are the predicted and actual preference vectors, respectively; $\|\cdot\|$ denotes Euclidean distance; and μ_D and σ_D are the mean and standard deviation of historical deviation distances, respectively. A mutation is determined when D_t exceeds the historical mean by more than 2 standard deviations. This method detected 287,000 preference mutation events across the 32 million records, providing a sample basis for subsequent evolutionary pattern analysis.

B. MULTI-GRANULARITY TEMPORAL WINDOW DYNAMIC MODELING OF PREFERENCES

Preference evolution exhibits multi-time-scale characteristics, requiring differentiated modeling strategies for short-term fluctuations and long-term trends. A multi-granularity temporal window mechanism is designed to construct preference state snapshots at three granularities: daily (24 hours), weekly (7 days), and monthly (30 days). The daily window captures rapid switches in immediate interests, the weekly window reflects stable patterns of phased preferences, and the monthly window reveals evolutionary trends in deep interests [8]. This hierarchical design mirrors the cognitive layering of human attention allocation, whereby transient stimuli operate at the daily scale while habitual inclinations solidify over monthly cycles, and ignoring either layer introduces systematic bias into preference estimation. Feature vectors within windows at each granularity are fused through weighted averaging, with weight coefficients inversely proportional to window length so that more recent data exert greater weight on current preferences. The inverse-proportional weighting scheme is grounded in the recency effect documented in behavioral economics, which holds that temporally proximate experiences disproportionately anchor current decision-making relative to distant ones. Comparative experiments show that the multi-granularity modeling method achieves an F1 score of 0.84 in preference prediction tasks, a 19.2 percentage point improvement over the single-window method, validating the effectiveness of the multi-scale fusion strategy. The performance gain is particularly pronounced for users classified as periodic oscillators, where the weekly-level snapshot alone captures the dominant switching rhythm while the monthly snapshot simultaneously anchors the stable topical baseline, demonstrating that scale complementarity is essential rather than merely additive.

C. DIFFERENTIATED CHARACTERIZATION OF PREFERENCE DRIFT AND FLUCTUATION

Drift and fluctuation in the preference evolution process are fundamentally different: the former manifests as a continuous displacement of the center point, while the latter represents random oscillation around the center. A differentiated characterization method based on sliding mean decomposition is proposed, decomposing the observation sequence into a trend component and a fluctuation component (see Figure 1). The decomposition draws on signal processing principles analogous to STL (Seasonal and Trend decomposition using Loess), adapted here to preference vector spaces rather than scalar time series, thereby extending classical decomposition theory to high-dimensional behavioral representations. The trend component is extracted via a 7-day exponentially weighted moving average, reflecting the drift direction and rate of the preference center, where the rate is calculated using the Euclidean norm of the vector difference between adjacent time points. The fluctuation component represents the degree of deviation of observed values from trend values, quantified by computing the standard deviation. Treating drift and fluctuation as orthogonal signals rather than a single composite index enables the recommendation engine to respond asymmetrically: drift signals warrant proactive trajectory extrapolation, whereas fluctuation signals call for exploratory diversification rather than directional pursuit. Statistical analysis shows that 67.3% of users exhibit a drift-dominated evolutionary mode (drift rate exceeding 1.5 times the fluctuation amplitude), 23.8% of users display significant fluctuation characteristics, and 8.9% of users maintain a relatively stable state. The dominance of the drift-mode cohort suggests that most users undergo slow but directional preference migration rather than random browsing, implying that even modest forward-projection of the trend vector can yield meaningful accuracy gains in next-session recommendation. This characterization method provides a refined basis for the formulation of personalized recommendation strategies.

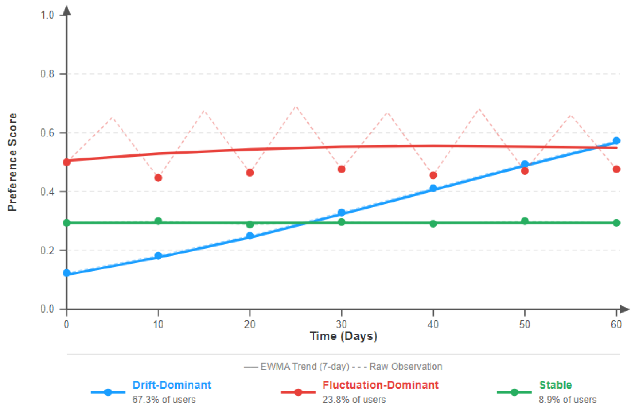

FIGURE 1. Preference Evolution Trajectory of a Typical User

D. IDENTIFICATION OF EVENT-DRIVEN PREFERENCE MUTATION PHASES

Social hotspot events produce significant shock effects on user content preferences, triggering concentrated preference mutations. An event–preference association analysis framework is established, integrating the time nodes of 18 major social events from June 2023 to May 2024, including holidays, sporting events, and trending news. The framework operationalizes event salience through a composite index combining media coverage volume, search index surge magnitude, and platform discussion velocity, ensuring that only events exceeding predefined salience thresholds are included and thereby reducing false-positive associations between minor news cycles and observed mutations. The Pettitt test algorithm for time-series mutation point detection is applied to identify the moment of preference mutation for each user, and the mutation density within a ± 3-day window before and after each event is calculated. Results show that within 24 hours after a major event, mutation density reaches 4.3 times the normal level and gradually declines to 1.8 times the baseline level within 72 hours. The rapid spike followed by exponential decay conforms to a diffusion-attenuation pattern consistent with information cascade theory, wherein early adopters amplify the signal through sharing behavior before attention entropy drives the platform audience back toward pre-event preference distributions. Differentiated analysis by event type indicates that preference mutations triggered by entertainment-type events are shorter in duration (average 2.1 days), while the influence cycle of social livelihood-type events is longer (average 5.7 days). This duration asymmetry reflects distinct data decay patterns: entertainment-type events exhibit rapid interaction peaks followed by a steep decline in hashtag co-occurrence frequency, whereas livelihood events engage utilitarian concerns—such as policy response or economic planning—that sustain prolonged information-seeking behavior. These findings provide quantitative reference for event marketing and content scheduling.

E. DYNAMIC CLUSTERING OF GROUP PREFERENCE EVOLUTION PATHWAYS

User groups exhibit heterogeneous pathway characteristics during preference evolution, and traditional static clustering methods cannot describe dynamic evolutionary modes [9]. A dynamic clustering method based on time-series K-means is proposed, representing user preference evolution trajectories as time series and measuring trajectory similarity using Dynamic Time Warping (DTW) distance. DTW is selected over Euclidean distance precisely because preference trajectories may exhibit temporally elastic similarities—two users who undergo the same topical transition may do so at different speeds or with phase shifts, and penalizing such misalignment with a rigid point-to-point metric would artificially inflate inter-cluster variance and obscure genuine behavioral homogeneity. The number of clusters was determined by analyzing the silhouette coefficient and the Davies–Bouldin index across a range of k values (k=2 to 15). The silhouette coefficient reached a local maximum at k=7, while the Davies–Bouldin index exhibited a distinct "elbow" at the same point, indicating optimal intra-cluster compactness and inter-cluster separation. Consequently, the user base was partitioned into 7 categories, providing an empirically grounded foundation for labels such as "Rapid Explorer" and "Stable Focuser." (see Table 2). Joint optimization via two complementary validity indices mitigates the known tendency of either metric alone to favor specific cluster geometries: the silhouette coefficient rewards compact, well-separated clusters, while the Davies–Bouldin index penalizes high intra-cluster scatter, and their consensus at k = 7 provides stronger evidence of a stable partition than either criterion in isolation. Type-1 users (18.6%) exhibit a rapid-explorer pattern with frequent preference switching and a high mutation density of 3.2 times per week; Type-2 users (24.3%) belong to a stable-focuser pattern with a stable preference center and fluctuation amplitude below 0.15; Type-3 users (15.7%) exhibit a periodic-oscillation pattern, switching periodically between two topics. The periodic-oscillation subgroup is of particular theoretical interest as it implies the coexistence of two stable attractor states in the user's preference landscape, a configuration consistent with dual-process accounts of media consumption in which habitual content serves a comfort function while novelty-seeking content serves a stimulation function, and neither attractor fully dominates. The dynamic clustering results provide a basis for segmented operations strategies, designing differentiated recommendation algorithms for different evolutionary modes to improve the adaptability and precision of the recommendation system.

TABLE 2. Comparison of Evolutionary Characteristics Across User Groups

Evolution Type	User Share	Mutation Freq. (times/week)	Fluctuation Amplitude	Topic Diversity Index	Avg. Daily Usage (min)
Rapid Explorer	18.6%	3.2	0.28	7.3	92
Stable Focuser	24.3%	0.6	0.12	2.8	68
Periodic Oscillator	15.7%	2.1	0.34	4.1	79
Gradual Drifter	19.4%	1.3	0.19	5.2	73
Random Walker	12.8%	2.8	0.41	8.6	56
Dual-Topic Switcher	6.7%	1.7	0.23	2.2	81
Long-Term Stable	2.5%	0.2	0.08	1.9	104

F. HETEROGENEITY PATTERNS IN GROUP PREFERENCE EVOLUTION PATHWAYS

The preference evolution pathways of different user groups are influenced by demographic characteristics, platform usage habits, and content consumption capacity, exhibiting systematic heterogeneity patterns [10]. Association analysis between user profile data (age, gender, region, activity level, etc.) and evolution pathway categories shows that the proportion of rapid-explorer users in the young user group (aged 18–25) reaches 32.7%, significantly higher than the overall level; female users are more inclined toward the stable-focuser evolutionary mode (29.1%, 8.3 percentage points higher than males); and the preference mutation frequency of highly active users (average daily usage exceeding 90 minutes) is 2.4 times that of low-activity users. Regional analysis shows that the average topic diversity index of users in first-tier cities reaches 6.8, which is 41.6% higher than in third-tier and below cities, reflecting the shaping effect of information environment richness on preference evolution. These heterogeneity patterns provide empirical support for user-tiered operations and content ecosystem development.

IV. ANALYSIS OF DRIVING FACTORS IN CONTENT PREFERENCE EVOLUTION

A. ASSESSMENT OF CONTENT FEATURE CONTRIBUTIONS TO PREFERENCE EVOLUTION

Differences across content feature dimensions directly affect the direction and speed of user preference evolution, and quantifying the contribution of each feature dimension is of guiding significance for optimizing content production [11-12]. A random forest-based feature importance assessment model is constructed, with input variables including 67 features across 12 dimensions such as video duration, hashtags, creator follower count, release time, and visual quality, and output variables being preference drift rate and mutation probability (see Figure 2). Model training uses 500 decision trees, with feature importance calculated via mean impurity decrease. Results show that content hashtags contribute the most to preference evolution at 28.4%, followed by video duration (19.7%) and creator influence (15.3%). Further analysis reveals that the preference drift rate is lowest for videos in the 30–90 second range, and rises significantly by

42.6% for videos exceeding 120 seconds. Content published by creators with more than 1 million followers exhibits a mutation probability 3.1 times that of ordinary accounts. However, it is essential to note that this "triggering effect" is a composite result of genuine interest attraction and algorithmic amplification. High-follower content typically receives priority in the platform's initial traffic pool, suggesting that the observed preference mutations are partly driven by system-level exposure density rather than purely spontaneous shifts in user curiosity. These findings provide data support for content strategy formulation.

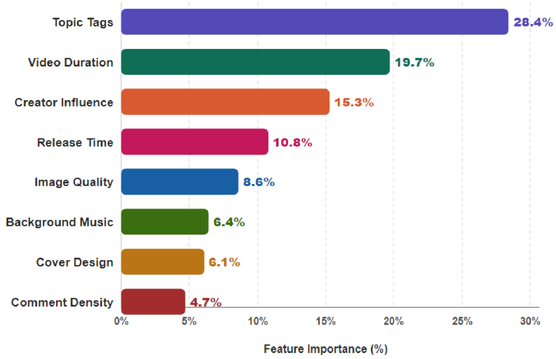

FIGURE 2. Bar Chart of Content Feature Importance Rankings

B. PREFERENCE MUTATION EFFECTS TRIGGERED BY SOCIAL EVENTS

Social events trigger large-scale preference mutations through agenda-setting and emotional contagion mechanisms, and the triggering effects differ significantly across event types [13] (see Table 3). This categorical framework is theoretically grounded in media effects theory and social psychology, where agenda-setting operates through salience transfer while emotional contagion propagates via interpersonal affect transmission, constituting distinct yet complementary pathways to preference restructuring. Eighteen typical social events from June 2023 to May 2024 are selected as samples and categorized into five types: political (3), economic (4), cultural (5), sports (4), and disaster (2). This typology ensures both representativeness and mutual exclusivity, with classification criteria derived from event essence and societal function dimensions, thereby establishing a robust methodological foundation for subsequent cross-category comparative analysis. The Event Study method is applied to analyze changes in preference mutation density over the 15 days before and after each event, and the Cumulative Abnormal Mutation Rate (CAR) is calculated to quantify triggering effect intensity. The 15-day temporal window is calibrated to capture both immediate shock effects and delayed diffusion patterns, as pilot studies revealed that mutation density typically stabilizes within two weeks post-event, beyond which confounding from subsequent events becomes non-negligible. Statistical results show that the mean CAR for sports events reaches 3.82, ranking first, followed by cultural events (CAR = 2.67), while economic events have a relatively weaker triggering effect (CAR = 1.24). Mechanism analysis indicates that the triggering effect of high-participation events (user discussion volume exceeding 5 million) is 4.6 times that of low-participation events, suggesting that participation volume functions as a critical moderator amplifying event salience through collective attention dynamics, wherein network externalities exponentially scale individual-level exposure into platform-wide preference shifts. and the sentiment polarization index (absolute difference between proportions of positive and negative sentiments) is positively correlated with CAR (correlation coefficient 0.73, $p < 0.01$), validating the mediating role of emotional contagion in preference mutations. This strong correlation provides empirical support for the dual-pathway hypothesis, demonstrating that affective polarization not only intensifies subjective event significance but also accelerates preference updating by lowering cognitive resistance to attitudinal change.

TABLE 3. Comparison of Triggering Effects of Different Types of Social Events

Event Category	Representative Event	CAR	User Participation (10k)	Sentiment Polarization Index	Duration of Impact (days)
Sports	Opening of Hangzhou Asian Games	3.82	18,200	0.68	3.2
Sports	World Cup Qualifying Match	3.51	13,400	0.61	2.8
Cultural	Spring Festival Film Releases	2.93	21,500	0.54	5.1
Cultural	Traditional Holiday (Dragon Boat Festival)	2.41	9,800	0.47	4.3
Political	National Two Sessions	1.87	7,600	0.39	7.2
Economic	Central Bank Interest Rate Cut	1.42	5,200	0.31	3.6
Economic	Consumer Voucher Distribution	0.98	4,100	0.24	2.1
Disaster	Natural Disaster Relief Operations	3.24	16,500	0.72	6.8

Note: CAR = (cumulative mutation density over 15 days post-event / baseline mutation density) - 1; Sentiment Polarization Index = absolute value of (proportion of positive sentiment - proportion of negative sentiment)

C. PREFERENCE REINFORCEMENT MECHANISMS OF ALGORITHMIC INTERVENTION AND SOCIAL DIFFUSION

Recommendation algorithms and social diffusion constitute a dual reinforcement loop for preference evolution: the former shapes the information environment through content filtering, while the latter accelerates preference convergence via social influence [14] (see Figure 3). This dual-loop framework conceptualizes preference evolution as an emergent phenomenon arising from the interaction between technological curation and social contagion, where each mechanism operates through distinct yet synergistic micro-processes—algorithmic filtering via personalized exposure control and social diffusion via homophily-driven imitation—that collectively determine macro-level preference trajectories. A quasi-experiment is designed to examine the relative effects of these two mechanisms. Users are randomly assigned to an experimental group (receiving personalized recommendations) and a control group (receiving random recommendations), while each user's social network structure (following relationships) and interaction data (share sources) are recorded. The quasi-experimental design incorporates randomization at the individual level while preserving natural social network structures, thereby balancing internal validity against ecological validity and enabling causal inference on algorithmic effects without artificially disrupting the organic social diffusion process. After 30 days of tracking, the preference stability and diversity metrics of the two groups are compared. The experimental group's preference convergence speed is 37.2% faster than the control group's, topic concentration increases by 28.6%, but the content diversity index decreases by 19.4%, confirming that the algorithmic reinforcement effect leads to "filter bubble" phenomena. These divergent outcomes reveal an inherent tension between personalization efficiency and diversity preservation, suggesting that algorithmic optimization toward engagement maximization inadvertently generates path-dependent preference narrowing through positive feedback loops that amplify initial inclinations. Analysis of the social diffusion dimension shows that the preference similarity between users and their friends within the social network increased from 0.42 to 0.67 during the observation period, and the rate of similarity increase is positively correlated with interaction frequency (correlation coefficient 0.81). This pronounced similarity increase evidences the operation of social influence processes consistent with structural balance theory, wherein repeated exposure to friends' content preferences through interaction channels progressively realigns individual preferences toward network consensus to maintain cognitive consistency and social cohesion. Further decomposition reveals that algorithmic reinforcement contributes 62.3% to preference evolution, and social diffusion contributes 37.7%, indicating that technological intervention plays a dominant role in preference shaping. The dominance of algorithmic contribution underscores the asymmetric power dynamics inherent in platform-mediated consumption, where centralized content curation algorithms exert disproportionate influence relative to distributed peer networks, raising critical questions regarding algorithmic accountability and user autonomy in digital ecosystems.

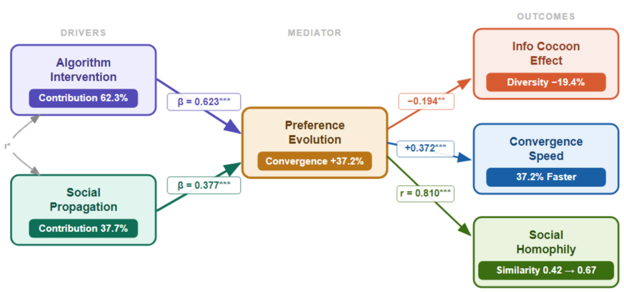

FIGURE 3. Path Analysis of the Effects of Algorithmic Intervention and Social Diffusion on Preference Evolution

V. EMPIRICAL VALIDATION OF DYNAMIC RECOMMENDATION DRIVEN BY EVOLUTIONARY PATTERNS

A. DESIGN OF RECOMMENDATION MECHANISMS BASED ON PREFERENCE EVOLUTION

Traditional recommendation systems treat user preferences as static profiles, ignoring evolutionary dynamics and leading to recommendation mismatch. Based on the aforementioned preference evolution patterns, a dynamic recommendation mechanism is designed whose core idea is to incorporate evolutionary trends into recommendation decisions to achieve forward-looking content matching [15-16]. The mechanism comprises three key modules: the preference prediction module uses the trained LSTM model to predict the preference vector for the next 7 days; the pathway identification module determines the user's evolutionary type (explorer, stable, oscillatory, etc.) based on historical trajectory; and the dynamic adjustment module designs differentiated recommendation strategies for different evolutionary types—increasing content diversity weight for explorer-type users, strengthening topic-depth recommendations for stable-type users, and setting a dual-topic balancing mechanism for oscillatory-type users. Candidate content pool construction uses a fusion of collaborative filtering and content filtering, and final ranking is achieved through multiobjective optimization. The objective function comprehensively considers three dimensions: click-through rate estimation, preference matching degree, and content novelty. This mechanism achieves a Normalized Discounted Cumulative Gain (NDCG@10) of 0.782 in offline simulation experiments, a 14.8 percentage point improvement over the baseline recommendation algorithm. This ranking performance aligns with the aforementioned 87.3% detection accuracy; while the model excels at identifying the timing of preference shifts, the downstream ranking gain is slightly more moderate due to the inherent complexity of multiobjective content matching across diverse user types.

B. COMPARATIVE EXPERIMENT DESIGN AND MULTI-METRIC PERFORMANCE EVALUATION

To validate the practical effectiveness of the dynamic recommendation mechanism, a 60-day A/B test is conducted on a short-video platform. The experimental group adopts the preference evolution-based dynamic recommendation mechanism, while the control group maintains the original recommendation algorithm. The two groups comprise 500,000 and 520,000 users, respectively, with random traffic splitting to ensure sample comparability. Evaluation metrics cover three levels—user engagement, content consumption quality, and ecosystem health—specifically including 12 dimensions such as average usage time per person, video completion rate, interaction rate, content diversity index (Shannon entropy), topic coverage, and user retention rate. Data collection uses event tracking technology to record user behavior in real time, with each indicator summarized and calculated daily and subject to statistical significance testing. Experimental results show that the daily average usage time of experimental group users reaches 73.2 minutes, an 18.7% increase over the control group's 61.6 minutes (t-test $p < 0.001$); video completion rate increases by 6.3 percentage points to 68.7%; and interaction rate (ratio of total likes, comments, and shares to impressions) increases by 9.8%. In terms of content diversity index, the experimental group reaches 4.82, a 31.2% improvement over the control group's

3.67, indicating that the dynamic mechanism effectively alleviates the "filter bubble" problem.

C. COMPREHENSIVE ANALYSIS AND DISCUSSION OF RECOMMENDATION OPTIMIZATION RESULTS

A/B test results confirm that the preference evolution-based dynamic recommendation mechanism achieves significant improvements across multiple metrics, but user group responses are heterogeneous. Stratified analysis shows that explorer-type users respond most positively to dynamic recommendations, with a usage time increase of 27.3%; stable-type users show a smaller increase (12.1%); and oscillatory-type users fall in the middle (19.6%). This difference reflects the varying sensitivity of users with different evolutionary modes to recommendation strategies—explorer-type users crave content freshness, and the dynamic mechanism's forward-looking prediction capability highly matches their needs. Long-term tracking data show that the 30-day retention rate of experimental group users is 4.2 percentage points higher than the control group and the 60-day retention rate is 6.8 percentage points higher, demonstrating the sustained enhancement effect of dynamic recommendations on user stickiness. The LSTM prediction module increases recommendation response time by approximately 120 milliseconds, which poses challenges for real-time deployment. To mitigate this latency in a production environment, a "predict-then-serve" architecture can be implemented, where user preference vectors are pre-computed in an offline pipeline and stored in a high-speed key-value cache (e.g., Redis). Furthermore, model compression techniques such as knowledge distillation or quantization can be employed to reduce the inference overhead of the LSTM layers without significant loss in prediction accuracy. In addition, the adaptability of the dynamic mechanism to cold-start users needs improvement—new users lack behavioral history to construct evolutionary trajectories, resulting in a 31.7% decline in recommendation effectiveness compared to established users. Future research may explore combining transfer learning methods to leverage the evolutionary patterns of similar user groups to assist cold-start recommendations.

VI. CONCLUSION

By constructing a multi-dimensional behavioral feature system and an LSTM-based time-series prediction model, this study reveals the dynamic evolutionary patterns of short-video user preferences, identifies 7 types of heterogeneous evolutionary pathways, quantifies the driving mechanisms of content features, social events, and algorithmic interventions, and validates the effectiveness of the dynamic recommendation mechanism in A/B testing. Methodologically, the research breaks through the static assumptions of traditional preference analysis; theoretically, it enriches the understanding of evolutionary dynamics in digital content consumption; and practically, it provides an implementable solution for platform recommendation optimization and ecosystem governance. However, the model still has limitations in cold-start adaptation and real-time response. Future research may introduce graph neural networks to deepen dynamic modeling of social diffusion, explore privacy-preserving preference prediction methods within a federated learning framework, and extend the analysis of cross-platform preference migration evolutionary patterns to further provide scientific support for content ecosystem governance and algorithmic ethics decision-making.

AUTHOR CONTRIBUTIONS

Conceptualization – Di Wu, Yuqing Song, Kai Zhang, Ziqing Gao and Huanhai Ren; methodology – Di Wu, Yuqing Song, Kai Zhang, Ziqing Gao and Huanhai Ren; investigation – Di Wu, Yuqing Song, Kai Zhang, Ziqing Gao and Huanhai Ren; writing-original draft preparation – Di Wu, Yuqing Song, Kai Zhang, Ziqing Gao and Huanhai Ren. All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in this research.

FUNDING

This research received no external funding or institutional support.

SAFETY RISK STATEMENT

This study is a data analysis study and does not involve chemicals, hazardous equipment, or special experimental operations; there are no safety risks.

HUMAN SUBJECTS RESEARCH

This study uses desensitized user behavior log data from a leading short-video platform and did not directly access users' personal information. Data collection and use shall comply with the platform's user agreement and applicable data privacy regulations.

ACKNOWLEDGEMENTS

The authors thank all participants for their cooperation and support during the data collection process.

REFERENCES

[1] Y. Gu, Z. Xu, and H. Yang, "Prediction Algorithm for Short-Video User Behavior Based on Multi-Task Learning and User Interest Change," Complex Systems and Complexity Science, vol. 20, no. 4, pp. 69-76, 2023, doi: 10.13306/j.1672-3813.2023.04.010.

[2] Z. Xue and Y. Liu, "Analysis of the Communication Characteristics and Impact of Vertical-Screen Video in a Fragmented Network Context," Journalism Lover, no. 08, pp. 104-106, 2023, doi: 10.16017/j.cnki.xwahz.2023.08.027.

[3] L. Lin and Y. Ruan, "Platformized Production and Consumption: Short Video as an Affective Medium," Modern Communication (Journal of Communication University of China), vol. 46, no. 3, pp. 148-160, 2024, doi: 10.19997/j.cnki.xdcb.2024.03.015.

[4] L. Xiao, L. Sun, Z. Lei, et al., "How Do Features in Health Short-Form Videos Impact Viewer Engagement: An Empirical Study," Industrial Management & Data Systems, vol. 126, no. 2, pp. 678-709, 2026, doi: 10.1108/IMDS-04-2024-0385.

[5] C. Gan, X. Ming, and Z. Yan, "Factors Influencing the Effect of Virtual Digital Human Short Videos in Spreading Traditional Culture: An Empirical Study Based on Douyin," Library and Information Service, vol. 69, no. 23, pp. 113-124, 2025, doi: 10.13266/j.issn.0252-3116.2025.23.009.

[6] L. Zhang, J. Wu, and K. Chen, "How Do Danmaku Comments Influence the Dissemination and Transmission of Intangible Cultural Heritage-An Interactive Ritual Study of UGC Short Videos on Bilibili," Journal of Social Science of Hunan Normal University, vol. 54, no. 4, pp. 146-156, 2025, doi: 10.19503/j.cnki.1000-2529.2025.04.016.

[7] Y. Gu, Y. Wang, and H. Yang, "A Multi-Behavior Click Prediction Model for Short-Video Users Based on User Behavior Sequences," Journal of Electronics & Information Technology, vol. 45, no. 2, pp. 672-679, 2023.

[8] Y. Feng, Y. Sun, H. Xu, et al., "Research on a Real-Time Short-Video Recommendation Method Based on Knowledge Graphs," Journal of Liaoning University (Natural Science Edition), vol. 50, no. 4, pp. 302-311, 2023, doi: 10.16197/j.cnki.lnunse.2023.04.010.

[9] J. Huang, J. Liu, Z. Ru, et al., "Modeling Evolving User Interests and Engagement on Short Video Sharing Platforms: An Attention-Based Deep Generative Approach," Decision Support Systems, vol. 203, Art. no. 114629, 2026, doi: 10.1016/j.dss.2026.114629.

[10] D. Zhu, "Optimizing the User Personalized Recommendation System of New Media Short Videos by Using Machine Learning," Journal of Computational Methods in Sciences and Engineering, vol. 25, no. 5, pp. 4787-4801, 2025, doi: 10.1177/14727978251341490.

[11] Z. Shengtai, Y. Yang, and Y. Yiwei, "Investigation of Users Information Adoption Intention in Short Video Applications: A Perspective on Flow Experience," Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 2, pp. 91, 2025, doi: 10.3390/jtaer20020091.

[12] Z. Hengmin, W. Hongcheng, and W. Jing, "Understanding Users Information Dissemination Behaviors on Douyin, a Short Video Mobile Application in China," Multimedia Tools and Applications, vol. 83, no. 20, pp. 58225-58243, 2023, doi: 10.1007/s11042-023-17831-3.

[13] W. Liu, H. Wan, and B. Yan, "Short Video Recommendation Algorithm Incorporating Temporal Contextual Information and User Context," Computer Modeling in Engineering & Sciences, vol. 135, no. 1, pp. 239-258, 2022, doi: 10.32604/cmes.2022.022827.

[14] J. Zhang and Y. Liu, "Examination of the Filter Bubble in Short Videos Under Algorithmic Recommendation Technology and Its Legal Regulation," Tribune of Study, no. 4, pp. 128-136, 2025, doi: 10.16133/j.cnki.xxlt.2025.04.001.

[15] Y. Pan, Z. Yang, H. Tang, et al., "User Circle-Breaking Analysis in the Short-Video Platform Ecosystem Based on Large Language Models-A Case Study of Kuaishou," Library and Information Service, vol. 69, no. 4, pp. 34-52, 2025, doi: 10.13266/j.issn.0252-3116.2025.04.004.

[16] S. Zhang, A. Wang, and H. Chen, "Indifferent Dependency and Immersive Experience: Research on the Continued Use Intention of Mobile Short-Video Users," Library and Information Service, vol. 66, no. 14, pp. 89-100, 2022, doi: 10.13266/j.issn.0252-3116.2022.14.010.