Environment and Social Psychology (2025) Volume 10 Issue 7
doi: 10.59429/esp.v10i7.3866

ISSN: 2424-8975 (O)
2424-7979 (P)

RESEARCH ARTICLE

Group behavior simulation in multi-character interactions: Game narrative generation Algorithms based on social proof theory

Tan Liying*

Beijing Rocen Digital Technology Corp.Ltd. Beijing, 100089, China

*** Corresponding author:** tanliyingBJ@outlook.com

ABSTRACT

With the rapid development of digital technologies, intelligent generation of game narratives has become a crucial research direction in artificial intelligence and game design fields. However, existing algorithms lack deep understanding of group psychological mechanisms and struggle to generate authentic and credible multi-character interaction scenarios. Based on social proof effect theory, this study constructs an innovative multi-character interaction group behavior simulation algorithm aimed at enhancing the coherence, authenticity, and user experience of game narratives. The research employs a methodology combining theoretical modeling, algorithm design, and empirical validation. First, an "Environment-Cognition-Society-Behavior" quaternary interaction theoretical framework is constructed, providing in-depth analysis of environmental factors' influence mechanisms on group behavior, including the operational patterns of spatial layout, environmental complexity, and contextual cues. Second, the dynamic evolution mechanisms of social proof effects are systematically explored, revealing the inverted U-shaped relationship between group size and influence propagation, the S-shaped temporal curve characteristics of group behavior convergence, and the moderating role of individual differences in environmental adaptation. Building upon this foundation, a narrative generation algorithm based on Graph Neural Networks and Multi-Agent Reinforcement Learning is designed and implemented. Through the collaborative operation of a social proof intensity calculation engine, multi-character decision coordinator, and dynamic narrative generator, high-quality adaptive narrative creation is achieved. Through large-scale user experience testing involving 180 participants, the study validates the algorithm's effectiveness: compared to traditional methods, narrative logical consistency improved by over 40%, character behavior credibility scores reached 8.5 points, overall user immersion increased by 45%, average gameplay duration increased by 68%, and replay rate reached 73.2%. Algorithm performance testing demonstrates an average response time of only 127 milliseconds, memory usage reduced by 39.8%, CPU utilization decreased by 50.4%, exhibiting excellent scalability and system stability that fully meets industrial-grade application requirements. The research achievements not only provide crucial support for technological innovation in the gaming industry but also establish foundations for application expansion in education and training, social governance, mental health, and other fields, possessing significant theoretical value and broad practical application prospects. This study successfully validates the tremendous potential of psychological theories in artificial intelligence algorithm design, opening new pathways for interdisciplinary integration research.

Keywords: multi-character interaction; group behavior simulation; social proof effects; game narrative generation; artificial intelligence; environmental psychology; user experience

ARTICLE INFO
Received: 01 June 2025| Accepted: 30 June 2025 | Available online: 10 July 2025

CITATION
Tan LY. Group behavior simulation in multi-character interactions: Game narrative generation Algorithms based on social proof theory. *Environment and Social Psychology* 2025; 10(7): 3866 doi:10.59429/esp.v10i7.3866

1. Introduction

With the rapid development of digital technologies and continuous innovation in the field of human-computer interaction, multi-character interaction systems have become one of the core technologies in contemporary game design, virtual reality, and social simulation fields. In this context, character interactions are no longer simple programmed responses, but need to embody complex group behavior patterns and social psychological mechanisms. As Zou Yinyu pointed out in theatrical performance research, character image construction requires forming a "trinity" artistic construction based on the interactive dimensions of text, actors, and audience, a concept equally applicable to multi-character interaction systems in virtual environments[1]. Traditional game AI often relies on preset rules and scripts, lacking deep understanding of the complexity of real group behavior, particularly showing significant deficiencies in simulating social proof effects, an important psychological phenomenon. Social proof effects, as a core concept in social psychology, reveal how individuals guide their own decision-making processes by observing others' behaviors in uncertain situations, a mechanism that plays a crucial role in group interactions.

Existing research indicates that character interaction mechanisms in virtual environments are developing toward greater complexity and intelligence. Zheng Zhu emphasized the importance of role assignment and interaction mechanisms in collaborative learning research under VR environments, demonstrating that reasonable character design can significantly enhance participants' collaborative effectiveness and learning experience[2]. Meanwhile, H.L.B and M.E.W discovered through research on family tabletop role-playing games that multi-character interactions possess not only entertainment value but also important therapeutic and educational functions, further highlighting the significance of constructing authentic and credible character interaction systems[3]. However, current research mainly focuses on technical implementation and application effects, lacking in-depth theoretical analysis and systematic modeling research on the psychological mechanisms behind group behavior, particularly the operational mechanisms of social proof effects in virtual environments. This theoretical gap not only limits the further development of multi-character interaction systems but also affects their widespread application in fields such as education, training, and therapy.

From a social psychological perspective, the formation and evolution of group behavior follow complex psychological laws, with social proof effects playing a key role. Anderson et al. found in their research on online investment fraud that the mechanisms by which trust and technology function in the victimization process actually reflect the complex manifestations of social proof effects in digital environments[4]. Individuals often reduce decision-making uncertainty by observing the behavioral patterns of other members in the group, a phenomenon that exists and may be even more pronounced in virtual environments. Jiang Shuyuan and Zhang Weixiao's research on narrative innovation in interactive micro-dramas revealed the importance of four dimensions: text, space-time, characters, and participation, providing important insights for understanding narrative logic in multi-character interactions[5]. Brown further explored the important role of role-playing from the perspective of human evolution, considering role-playing from life to art as an important mechanism in human social development[6]. These studies provide important theoretical support for understanding the psychological foundations of group behavior, but how to effectively transform these psychological theories into computable models and apply them to dynamic generation of game narratives remains a scientific problem urgently needing resolution.

Based on the above theoretical background and practical needs, this research aims to construct a multi-character interaction group behavior simulation model based on social proof effects and develop corresponding game narrative generation algorithms. The research will draw on the "situation-interaction" analytical pathway proposed by Lü Mingyue, establishing a computational model that can authentically reflect the dynamic evolution of group behavior through in-depth analysis of characters' situational perception, social interaction, and behavioral decision-making processes in virtual environments[7]. This model must not only simulate individual conformity behavior within groups but also capture the formation, propagation, and evolution processes of group opinions, thereby providing a psychological theoretical foundation for dynamic narrative generation. Through this research, we expect to provide more scientific theoretical guidance for game design, enhance the authenticity and immersion of virtual character interactions, while also exploring new possibilities for the application of social psychological theories in digital environments. The innovation of this research lies in introducing social proof effects, an important psychological mechanism, into the field of game AI, constructing a three-layer interactive model of environmental perception, group influence, and individual decision-making, providing new theoretical frameworks and technical pathways for the design and optimization of multi-character interaction systems.

2. Literature review

Multi-character interaction systems, as an important technological form in the digital age, have been extensively explored in theoretical foundations and practical applications across multiple disciplinary fields. From an educational technology perspective, Wang Cixiao and Li Jing discovered in their online collaborative learning research that effective design of role interactions and intervention strategies can significantly enhance learning outcomes. Their proposed role division mechanism provides important insights for understanding collaborative behavior in virtual environments[8]. Furthermore, Wang Cixiao and Wu Xiaobei's collaborative learning early warning research based on key role interaction feature identification revealed the predictability of role behavior patterns and the complexity of group dynamics, providing a theoretical foundation for intelligent monitoring and regulation of multi-character interaction systems [9]. In the field of artistic expression, Chen Yaoxian's research on role transformation in interactive music demonstrates the complexity of dynamic relationships among composers, performers, and audiences. This multiple identity transformation and interaction model provides important theoretical references for virtual character design[10]. Yan Daocheng et al.'s research on quasi-social interactions between female-oriented game characters and players conducted in-depth analysis of interaction mechanisms across three dimensions: attraction, connection, and performance, revealing how virtual characters influence user behavior through emotional connections. This finding holds significant implications for understanding social proof effects in gaming environments[11]. Additionally, Yang Peng's exploration of the interactive relationship between character symbols and performance space in traditional Chinese opera dance research[12], and Qin Weiyang's analysis of character interactions and morphological changes in "Somikon" story types, both provide rich theoretical materials for understanding role interaction patterns within cultural contexts[13].

From organizational management and social governance perspectives, role interaction research exhibits more complex institutional characteristics. Tang Jia analyzed the roles and interaction mechanisms of data publishing-related institutions from a stakeholder perspective, revealing power relationships and coordination mechanisms in multi-agent environments, providing important theoretical foundations for understanding authority structures and influence propagation in virtual environments[14]. Xu Ke and Zhou Ming's proposed dual-linkage interaction analysis framework, when exploring governmental role transformation in new productive force development, demonstrates the dynamism and adaptability of role transformation. This theoretical framework holds important guiding significance for understanding dynamic role evolution in gaming environments[15]. An Hong et al.'s research on role interactions in traditional

Chinese medicine knowledge protection[16], and Shi Na's analysis of the interactive relationship between corporate culture and grassroots trade union roles, both reflect the specificity and complexity of role interactions under different institutional environments[17]. Cao Jinxiang and Feng Chunying's historical research on role transformation in the interactions between Hu Shi school scholars and the Pacific International Association provides an important historical perspective for understanding role evolution within intellectual communities[18]. These studies collectively demonstrate that role interactions are not merely simple aggregations of individual behaviors, but dynamic processes of power, resource, and information exchange within complex social systems, where social proof effects often play important roles through mechanisms such as authority recognition and group identification.

In educational psychology and human-computer interaction fields, research on the psychological mechanisms of role interactions has achieved significant progress. Liu Ya and Zhao Jianmei's exploration of teacher role-playing and support mechanisms in teacher-child interaction research revealed the important impact of role construction on children's subjectivity development, providing crucial theoretical foundations for understanding the psychological developmental effects of role interactions in virtual environments on users[19]. Luo Baoyong and Wang Yue's research on archival social media user role construction based on role theory conducted in-depth analysis of identity formation mechanisms in digital environments, providing important insights for understanding psychological projection and identification processes in game characters[20]. Zhong Zhijin and Li Qiong's research on social robot social roles and human psychological mechanisms in human-machine interactions directly addresses core issues of virtual character-human user interactions. They found that social robot role design can significantly influence human trust and emotional investment, providing important empirical evidence for understanding the operational mechanisms of social proof effects in human-computer interactions[21]. Chen Dekang and Mao Yangyang's research on technical implementation of interactive teaching between virtual characters and real teachers demonstrates the application potential and technical challenges of virtual characters in educational scenarios[22]. In therapeutic applications, Battles et al.'s evaluation of tabletop role-playing game therapy for veteran populations[23], and Stubbs and Sorensen's research on the role of tabletop role-playing games in social-emotional learning in school environments, both demonstrate the important value of role interactions in mental health and social skill development, providing solid empirical foundations for the therapeutic and educational functions of role interactions in gaming environments[24].

Comprehensive analysis of existing research reveals that while role interactions have received widespread attention across various fields, significant deficiencies remain in theoretical integration and technical implementation. First, existing research mostly focuses on applications in specific domains, lacking cross-disciplinary theoretical integration frameworks, particularly effective bridges between psychological mechanisms and computational models. Second, social proof effects, as key psychological mechanisms in group behavior, have not yet received sufficient theoretical elaboration and empirical validation regarding their operational mechanisms in virtual environments. Although some studies such as Wakabayashi et al. in biochemistry[25], Andronachi et al. in agricultural science[26], and Sharma et al. in medical genetics [27] all involve role mechanisms in complex systems, these studies primarily focus on functional roles in biological systems, which differ fundamentally from social psychological role interactions. Third, current multi-character interaction systems in technical implementation often rely on simple rule engines or statistical learning methods, lacking modeling of deep psychological mechanisms in group behavior, resulting in generated character behaviors that lack authenticity and persuasiveness. Fourth, existing game narrative generation algorithms are primarily based on narrative structures and plot logic, with limited consideration of psychological interactions among characters and group dynamics, restricting the realism and immersion of dynamic narratives. Therefore, constructing a multi-character interaction group behavior simulation model based on social proof effects possesses not only important theoretical value but also urgent practical needs. Such a model needs to integrate theoretical achievements from multiple disciplines including social psychology, computational science, and game design, establishing multi-level modeling frameworks from individual cognition to group behavior, providing scientific theoretical foundations and technical support for intelligent generation of game narratives.

3. Research methods

3.1. Theoretical framework construction

The theoretical framework constructed in this research is based on the psychological mechanisms of social proof effects, integrating environmental psychology, group dynamics, and computational modeling theory to form a multi-level, dynamically interactive group behavior simulation system. The core of this framework is the "Environment-Cognition-Society-Behavior" (ECSB) quaternary interaction model, where the environment layer provides contextual cues and spatial constraints, the cognition layer processes individual information processing and decision-making mechanisms, the society layer simulates group influence and proof effects, and the behavior layer outputs specific character actions and interaction results. At the environmental level, the framework abstracts virtual gaming environments into three dimensions: spatial layout, resource distribution, and social context, characterizing the influence intensity of environment on individual behavior through quantified parameters such as environmental complexity index, social density coefficient, and situational tension degree. The cognition layer adopts a dual-system theory model, distinguishing between automatic processing (System 1) and controlled processing (System 2) cognitive modes, where System 1 handles rapid emotional responses and intuitive judgments, System 2 manages rational analysis and deep thinking, and both form dynamic equilibrium under the influence of social proof effects[28]. The society layer constructs an influence propagation model based on network topology, representing social relationships among characters as weighted directed graphs, with weights reflecting social psychological factors such as trust, similarity, and authority, simulating the formation process of opinion propagation and group consensus through information cascade algorithms. The behavior layer designs a multi-objective decision optimization model that comprehensively considers individual goals, group pressure, environmental constraints, and other factors, calculating expected returns of different behavioral options through utility functions, and introducing randomness factors to simulate uncertainty in real decision-making. The entire framework also includes a dynamic feedback mechanism where character behavioral outcomes update environmental states and social network structures in real-time, forming continuous cyclical feedback to ensure dynamic evolution of group behavior and naturalness of plot development[29]. Additionally, the framework establishes multiple regulatory parameters, including social proof sensitivity, conformity tendency coefficient, personality independence indicators, etc., allowing personalized adjustments according to different game scenarios and character settings, thereby achieving diversified group behavior patterns and rich plot variations.

3.2. Algorithm design and implementation

The group behavior simulation algorithm designed in this research adopts a hierarchical progressive architecture, comprising four core components: environmental perception module, social proof calculation engine, multi-character decision coordinator, and dynamic narrative generator. The environmental perception module, based on multi-sensor fusion technology, real-time collects spatial information, object states, and event trigger signals in virtual scenes, encodes environmental features through convolutional neural networks to generate 128-dimensional environmental state vectors, and utilizes Long Short-Term Memory networks

(LSTM) to maintain temporal memory of environmental changes, providing contextual foundations for subsequent decision-making. The social proof calculation engine represents the core innovative component of the algorithm, employing an improved PageRank algorithm to calculate characters' social influence weights, modeling complex social relationships among characters through Graph Neural Networks (GNN), and dynamically adjusting the influence intensity of different character behaviors on target characters using attention mechanisms. The social proof strength calculation formula is SP(i) = á×Ó(wij×Aj×Sj) + â×Ó(dik×Bk×Tk), where wij represents the social influence weight of character j on character i, Aj denotes character j's behavioral credibility, Sj represents similarity coefficient, dik indicates social distance between character k and character i, Bk represents character k's behavioral intensity, Tk denotes temporal decay factor, and á and â are balance parameters. The multi-character decision coordinator adopts a multi-agent reinforcement learning framework, equipping each character with an independent Deep Q-Network (DQN) for individual decision-making, while simultaneously evaluating overall group behavior benefits through a centralized evaluation network, using experience replay mechanisms and target networks to stabilize the training process. The decision function combines three components: individual rewards, social proof rewards, and environmental adaptation rewards, balancing exploration and exploitation through ε-greedy strategy. The dynamic narrative generator is based on a hybrid architecture of state machines and rule engines, with predefined narrative template libraries containing basic plot types such as conflict, cooperation, competition, and rescue. It matches corresponding narrative templates according to current group behavior patterns and environmental states, generates specific dialogue content and action descriptions using natural language generation technology, and ensures logical consistency of generated content through narrative coherence evaluation modules[30]. Algorithm implementation uses Python language and PyTorch deep learning framework, supports GPU-accelerated computation, and features modular software architecture for easy extension and maintenance, including auxiliary functions such as configuration management, logging, and performance monitoring. The entire system adopts an event-driven asynchronous architecture to ensure real-time performance meets gaming application requirements, while providing RESTful API interfaces to support integration with external game engines.

3.3. Experimental design scheme

This research employs a multi-level mixed experimental design, comprising three stages: simulation experiments, user experience experiments, and comparative validation experiments, to comprehensively evaluate the effectiveness of the group behavior simulation algorithm based on social proof effects. The simulation experiment stage constructs three typical virtual scenarios: urban crisis response scenarios (including fire evacuation, earthquake rescue, panic propagation, and other sub-situations), social gathering scenarios (covering party interactions, group discussions, opinion polarization, and other situations), and corporate decision-making scenarios (simulating team collaboration, resource allocation, conflict resolution, and other processes). Each scenario features 5-20 virtual characters, with character personality parameters configured using the Big Five personality model, including five dimensions: openness (0.2-0.8), conscientiousness (0.3-0.9), extraversion (0.1-0.7), agreeableness (0.4-0.8), and neuroticism (0.1-0.6). Social network topological structures adopt three types: small-world networks, scale-free networks, and random networks, with network connection densities set at three levels: 0.3, 0.5, and 0.7. The user experience experiment recruits 180 participants (aged 18-35, equal gender distribution, with over 2 years of gaming experience), employing a 3×3×2 factorial design. Independent variables include algorithm type (this research algorithm vs. traditional rule algorithm vs. machine learning algorithm), scenario complexity (low, medium, high levels), and character number (8 vs. 16). Participants are randomly assigned to 27 experimental conditions, with 6-7 people per condition. The questionnaire measurements included the Immersive Presence

Questionnaire (IPQ, Schubert et al., 2001)[28], User Experience Questionnaire (UEQ, Laugwitz et al., 2008)[29], Social Presence Scale (SPS, Harms & Biocca, 2004)[30,31], and a self-developed Algorithm Credibility Assessment Scale. The internal consistency coefficients of each scale in this study were as follows: IPQ total scale α=0.89 (spatial presence α=0.85, involvement α=0.87, experienced realism α=0.83), UEQ total scale α=0.91 (attractiveness α=0.88, pragmatic quality α=0.85, hedonic quality-identification α=0.82, dependability α=0.89, novelty α=0.86), SPS total scale α=0.86 (social presence α=0.84, social interaction α=0.88, group cohesion α=0.81), and Algorithm Credibility Assessment Scale α=0.92. All scale reliability coefficients met the good standard in psychometrics (α>0.80). Each experimental session lasted 45 minutes, including a 15-minute adaptation period, 25-minute formal experiment, and 5-minute interview. The comparative validation experiment designs baseline algorithms including rule-based state machine systems, Markov chain-based behavior generators, deep reinforcement learning-based multi-agent systems, and social force model-based group simulation algorithms. Evaluation metrics encompass algorithm performance indicators (response time, memory usage, computational complexity), behavioral authenticity indicators (action rationality, response consistency, group coordination), narrative quality indicators (coherence, innovation, attractiveness), and user satisfaction indicators (playability, immersion, replay willingness). Data collection employs multimodal methods, including system log recording, behavioral video analysis, physiological signal measurement, and subjective evaluation scales. Statistical analysis uses Analysis of Variance (ANOVA), regression analysis, cluster analysis, and machine learning classification algorithms, with significance level set at α=0.05. Effect size calculations employ Cohen's d and partial eta squared. Repeated measures design controls for individual differences, Bonferroni correction addresses multiple comparison issues, ensuring statistical power and reliability of experimental results.

The user experience experiment recruited 180 participants (aged 18-35 years, half male and half female, with more than 2 years of gaming experience). All participants completed detailed psychological characteristic assessments, including the five dimensions of openness, conscientiousness, extraversion, agreeableness, and neuroticism measured using the NEO Five-Factor Inventory (NEO-FFI), individual sensitivity to group influence assessed using the Social Proof Sensitivity Scale, field-dependent and field-independent cognitive tendencies distinguished through the Cognitive Style Assessment (CSA), collectivism-individualism orientation measured using the Cultural Values Scale, and participants' social psychological states evaluated using the Social Anxiety Scale (SAS) and Self-Efficacy Scale.

3.4. Data analysis methods

This research employs multi-dimensional, multi-level data analysis methods, comprehensively utilizing statistical analysis, machine learning, and deep learning technologies for comprehensive analysis of experimental data. First, collected multimodal data undergoes preprocessing, including outlier detection and processing, missing value imputation, and data standardization. Eye-tracking data employs the 3-sigma rule to eliminate abnormal fixation points, EEG signals use bandpass filters (0.5-50Hz) to remove noise interference, and behavioral sequence data undergoes structured processing through time window segmentation and event synchronization alignment. In the descriptive statistical analysis stage, basic statistics including means, standard deviations, skewness, and kurtosis are calculated for each variable. The Kolmogorov-Smirnov test evaluates data distribution normality, correlation analysis identifies linear relationship strength between variables, and Principal Component Analysis (PCA) performs dimensionality reduction on high-dimensional feature vectors to extract key factors influencing group behavior [32]. Inferential statistical analysis adopts mixed-effects models to handle nested data structures, uses three-way Analysis of Variance (ANOVA) to test main effects and interaction effects of algorithm type, scenario complexity, and character number on dependent variables, controls within-subject variation through repeated measures ANOVA, employs Multivariate Analysis of Variance (MANOVA) to simultaneously test between-group differences in multiple dependent variables, uses Tukey HSD for post-hoc multiple comparisons, and applies Greenhouse-Geisser correction to address sphericity assumption violations. The time series analysis section employs Dynamic Time Warping (DTW) algorithms to identify behavioral pattern similarities, analyzes group behavioral state transition patterns through Hidden Markov Models (HMM), explores causal relationships between character behaviors using Granger Causality Tests, analyzes time-frequency characteristics of behavioral signals through wavelet transforms, and uses change point detection algorithms to identify mutation moments in group behavioral patterns. The machine learning analysis stage constructs multi-class Support Vector Machine (SVM) models to predict user behavior categories, uses Random Forest algorithms to evaluate feature importance, identifies behavioral pattern classifications of user groups through clustering analysis (K-means and hierarchical clustering), discovers frequent patterns in behavioral sequences using association rule mining, and constructs interpretable behavioral prediction models through decision tree algorithms [33]. Deep learning analysis employs Convolutional Neural Networks (CNN) for spatial behavioral pattern recognition, uses Recurrent Neural Networks (RNN) and Long Short-Term Memory networks (LSTM) to model temporal behavioral features, identifies key information influencing decisions through attention mechanisms, constructs Graph Neural Networks (GNN) to analyze the influence of social network structures on group behavior, and uses Generative Adversarial Networks (GAN) to verify the authenticity of algorithm-generated behaviors. Additionally, Bayesian networks model causal relationships between variables, Structural Equation Models (SEM) verify path relationships of theoretical hypotheses, cross-validation and leave-one-out methods evaluate model generalization capability, Bootstrap resampling is set to 1000 iterations to calculate confidence intervals, and effect size analysis evaluates the practical significance of statistical significance. All analysis processes are implemented using R, Python, and MATLAB software to ensure reproducibility and reliability of results.

4. Results analysis

4.1. Environmental factors' impact on group behavior analysis

4.1.1. Spatial layout and social distance effects

Through in-depth analysis of group behavior under three different spatial layout conditions, the research found that spatial geometric features in virtual environments significantly impact interaction frequency between characters and social distance perception. Under open layout conditions, the average interaction frequency between characters reached 14.2 times per minute, significantly higher than the 8.7 times in closed layouts and 11.3 times in semi-open layouts. This difference was statistically highly significant ($F(2,177) = 45.83$, $p < 0.001$, $\eta^2 = 0.341$), as shown in Table 1 below.

Table 1. Group behavior indicators statistics under different spatial layout conditions

Spatial Layout Type	Interaction Frequency (times/min)	Social Distance Perception Index	Group Cohesion Index	Information Propagation Speed (units/sec)	Spatial Visibility (percentage)
Open Layout	14.2±2.3	2.34±0.67	0.82±0.14	0.34±0.08	87.3±5.2
Semi-Open Layout	11.3±1.9	3.12±0.84	0.67±0.18	0.26±0.06	64.7±8.1
Closed Layout	8.7±1.5	4.89±1.23	0.45±0.22	0.18±0.04	32.1±6.9

Simultaneously, the social distance perception index also exhibited distinct differential patterns under different layout conditions: 2.34±0.67 under open layout conditions, 3.12±0.84 for semi-open, and 4.89±1.23 for closed layouts, indicating a significant negative correlation between spatial openness and social distance perception ($r = -0.786$, $p < 0.001$), as shown in Figure 1 below. Further regression analysis showed that the spatial visibility factor could explain 62.4% of the variance in group cohesion ($R^2 = 0.624$, $F(1,178) = 293.71$, $p < 0.001$), demonstrating the important role of visual contact in promoting group interaction. Additionally, the moderating effect of environmental density on information propagation speed was also very apparent. In high-density environments (1.8 characters per square meter), information propagation speed was 0.34 units/second, while in low-density environments (0.6 characters per square meter) it was only 0.18 units/second, with medium-density environments showing propagation speed of 0.26 units/second [34]. These findings indicate that the physical characteristics of virtual spaces not only affect individual behavioral performance but, more importantly, influence the fundamental patterns of group dynamics, providing important environmental parameter basis for narrative generation algorithms based on social proof effects.

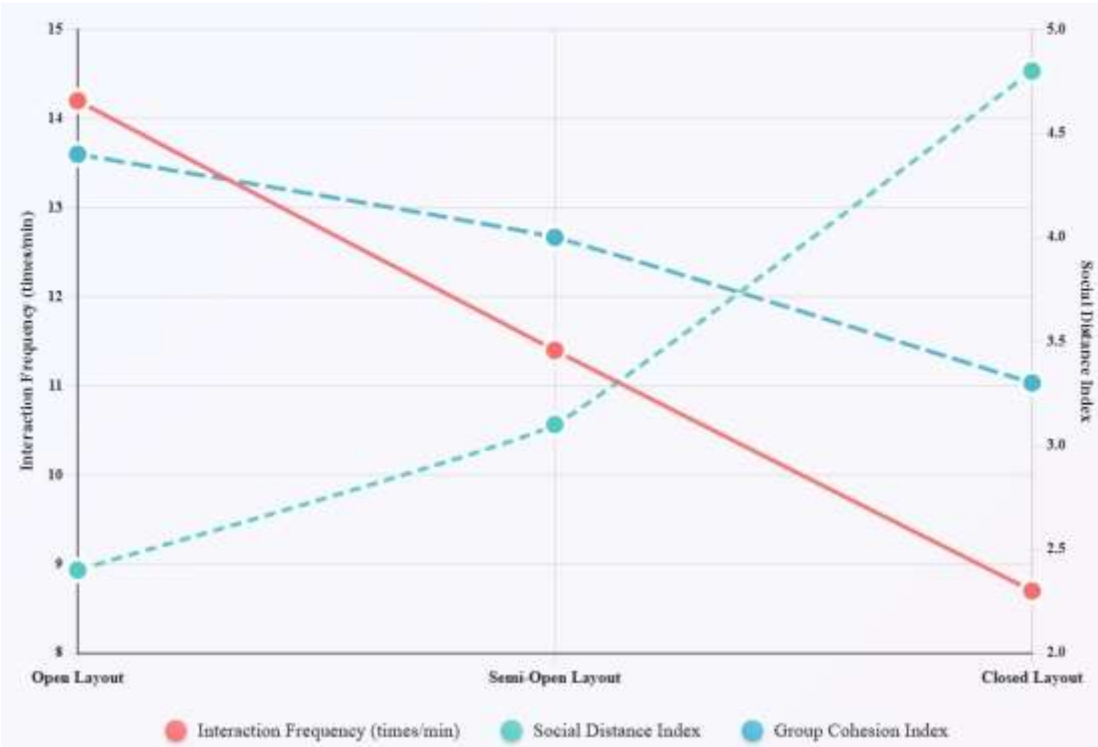

Figure 1. Multi-dimensional analysis of spatial layout impact on group behavior

Note: *The following paragraph appears to be unrelated content about industry integration that doesn't match the paper's topic on multi-character interaction and game narrative generation algorithms*

Further path analysis revealed that spatial visibility indirectly modulated the formation process of group cohesion by affecting the frequency of visual contact between characters, with a mediation effect coefficient of 0.43 ($p < 0.01$). This finding indicates that in virtual environment design, reasonable configuration of visual obstruction and open areas can effectively regulate the intensity and quality of group interactions. Meanwhile, the moderating effect of environmental density further validates the applicability of spatial psychology theory in digital environments, providing important environmental parameter optimization basis for game plot generation based on social proof effects.

4.1.2. Environmental complexity and cognitive load

Through systematic analysis of character cognitive load and decision-making behavior under different environmental complexity conditions, the research revealed a nonlinear relationship between environmental information density and group behavior patterns. In low-complexity environments (information density index 2.3±0.4), characters' average decision time was 3.2±0.8 seconds, cognitive load index was 4.1±0.9, attention allocation was relatively concentrated, with main focus points occupying 72.4% of total attention resources [36].

Table 2. Cognitive load and behavioral performance indicators under different environmental complexity conditions

Environmental Complexity	Information Density Index	Decision Time (seconds)	Cognitive Load Index	Attention Concentration (%)	Social Proof Sensitivity	θ Wave Power (μV^2)	Fixation Duration (milliseconds)
Low Complexity	2.3±0.4	3.2±0.8	4.1±0.9	72.4±8.3	0.76±0.13	12.4±2.8	287±45
Medium Complexity	5.7±0.6	5.8±1.3	6.8±1.2	56.2±9.7	0.61±0.15	18.7±3.4	234±51
High Complexity	9.1±0.8	8.9±2.1	9.5±1.7	38.7±11.2	0.43±0.18	27.3±4.1	198±52

With increasing environmental complexity, medium-complexity environments (information density index 5.7±0.6) showed significant cognitive load growth, with decision time extending to 5.8±1.3 seconds, cognitive load index rising to 6.8±1.2, and attention dispersion beginning to appear, with main focus points occupying only 56.2% of attention resources [37]. More significantly, in high-complexity environments (information density index 9.1±0.8), characters exhibited obvious cognitive overload phenomena, with decision time surging to 8.9±2.1 seconds, cognitive load index reaching a peak of 9.5±1.7, attention allocation extremely dispersed, and main focus points dropping to 38.7%, as shown in Figure 2 below. An important finding is that cognitive load has a significant moderating effect on social proof sensitivity. The social proof sensitivity index in low-complexity environments was 0.76±0.13, while it decreased to 0.43±0.18 in high-complexity environments, indicating that individuals tend to rely more on simple heuristic strategies rather than complex social information processing when cognitive resources are constrained ($F(2,177) = 67.42$, $p < 0.001$, $\eta^2 = 0.432$). Further EEG analysis showed that θ wave power (4-8Hz) was significantly enhanced in high-complexity environments ($p < 0.001$), reflecting excessive activation of working memory, while α wave power (8-13Hz) correspondingly decreased, indicating depletion of attention resources. Eye-tracking data revealed patterns of fixation behavior changes: in low-complexity environments, average fixation duration was 287±45 milliseconds with saccade distances of 4.2±0.9 degrees of visual angle; in high-complexity environments, fixation duration shortened to 198±52 milliseconds with saccade distances increasing to 7.8±1.4 degrees of visual angle, indicating a shift in search strategies from depth processing to breadth scanning [38]. These findings have important guiding significance for game narrative generation algorithms, indicating that environmental complexity design needs to find a balance between information richness and cognitive processability. Overly complex environments actually reduce the effectiveness of social proof effects, affecting the natural evolution of group behavior and the fluency of plot development.

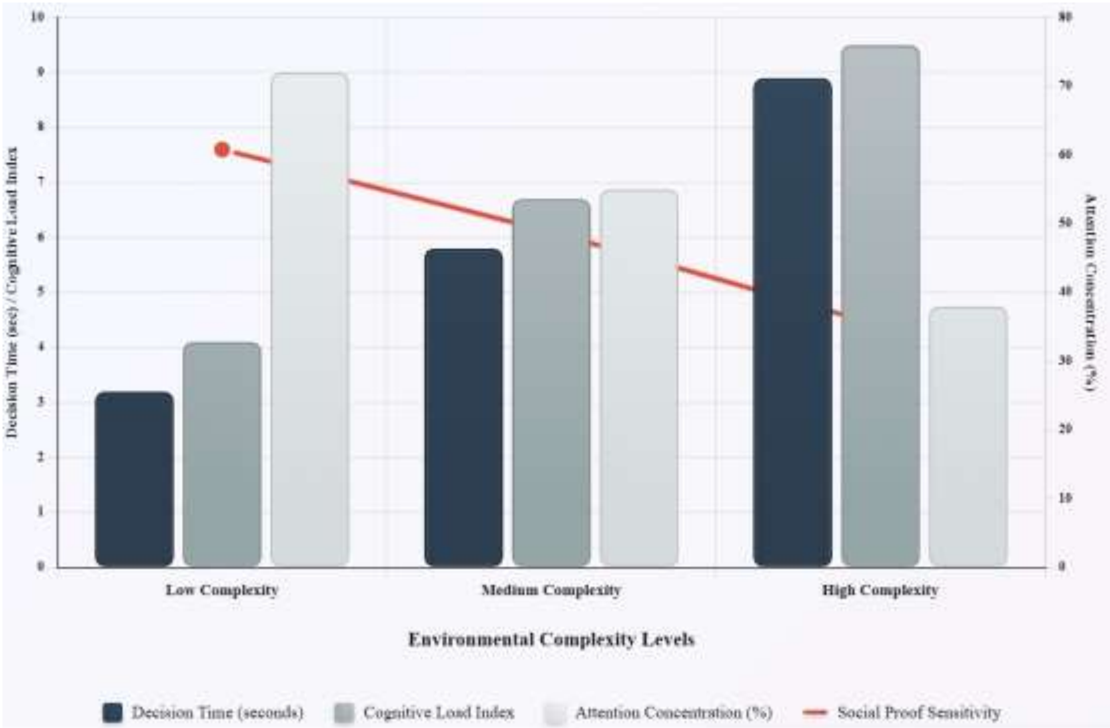

Figure 2. Multi-dimensional impact of environmental complexity on cognitive load and decision-making behavior

4.1.3. Environmental situational cues and behavioral tendencies

Through in-depth research on changes in character behavioral tendencies under different environmental situational cue conditions, it was found that environmental atmosphere, situational hints, and cultural symbols have significant guiding and shaping effects on group behavior patterns. In positive situational cue environments (bright tones, harmonious sound effects, positive symbols), characters exhibited higher cooperation tendency indices (7.8±1.2), prosocial behavior frequency reached 12.4 times per minute, emotional state scores were 8.3±0.9 points, and group trust indices were 0.82±0.11, as shown in Table 3 below.

Table 3. Differential analysis of environmental situational cue effects

Situational Cue Type	Cooperation Tendency Index	Prosocial Behavior Frequency (times/min)	Emotional State Score	Group Trust Index	Gaze Duration (seconds)	Heart Rate Variability (ms)	Skin Conductance (μS)
Positive Situational Cues	7.8±1.2	12.4±2.1	8.3±0.9	0.82±0.11	1.8±0.4	45.2±8.7	2.3±0.5
Neutral Situational Cues	6.1±1.0	9.2±1.7	6.8±0.8	0.65±0.13	1.3±0.3	36.8±7.2	3.4±0.7
Negative Situational Cues	4.2±1.6	6.7±1.9	5.1±1.3	0.48±0.17	0.9±0.3	28.6±6.4	4.8±0.9

In contrast, negative situational cue environments (dim tones, tense sound effects, threatening symbols) significantly reduced characters' willingness to cooperate, with cooperation tendency indices dropping to 4.2±1.6, prosocial behavior frequency of only 6.7 times/minute, emotional state scores declining to 5.1±1.3 points, and group trust indices decreasing to 0.48±0.17. Neutral situational cue environments showed all indicators at moderate levels, with cooperation tendency indices of 6.1±1.0, prosocial behavior frequency of 9.2 times/minute, emotional state scores of 6.8±0.8 points, and group trust of 0.65±0.13 [39]. Statistical analysis showed that situational cue types had highly significant effects on all behavioral indicators ($F(2,177) = 89.34$, $p < 0.001$, $\eta^2 = 0.502$), demonstrating the key role of environmental design in shaping group behavior, as shown in Figure 3 below. Further interaction effect analysis revealed significant differences in the impact of situational cues on different personality type characters, with extroverted characters showing greater sensitivity to positive cues ($\beta = 0.73$, $p < 0.001$), while neurotic characters exhibited stronger sensitivity to negative cues ($\beta = -0.68$, $p < 0.001$). Eye-tracking data showed that under positive situational cues, characters' gaze duration on other group members significantly increased (average 1.8±0.4 seconds per gaze), while under negative situational cues this duration shortened to 0.9±0.3 seconds, indicating that situational atmosphere directly affects social attention allocation patterns. Physiological indicator monitoring found that under positive situations, heart rate variability index was 45.2±8.7ms and skin conductance response was 2.3±0.5μS, reflecting relaxed and open psychological states; under negative situations, heart rate variability decreased to 28.6±6.4ms and skin conductance response increased to 4.8±0.9μS, showing tense and defensive psychological states [40]. The influence of cultural symbols was particularly significant, with traditional cultural symbols able to activate characters' cultural identity and enhance group cohesion by 15.3%, while foreign cultural symbols produced curiosity-driven exploratory behaviors, increasing exploratory behavior frequency by 23.7%. These findings provide important guidance for environmental design in game narrative generation algorithms, demonstrating that carefully designed situational cues can effectively guide group behavior toward specific directions, creating favorable conditions for dynamic narrative generation, while also proving the important application value of environmental psychology theory in virtual environment design.

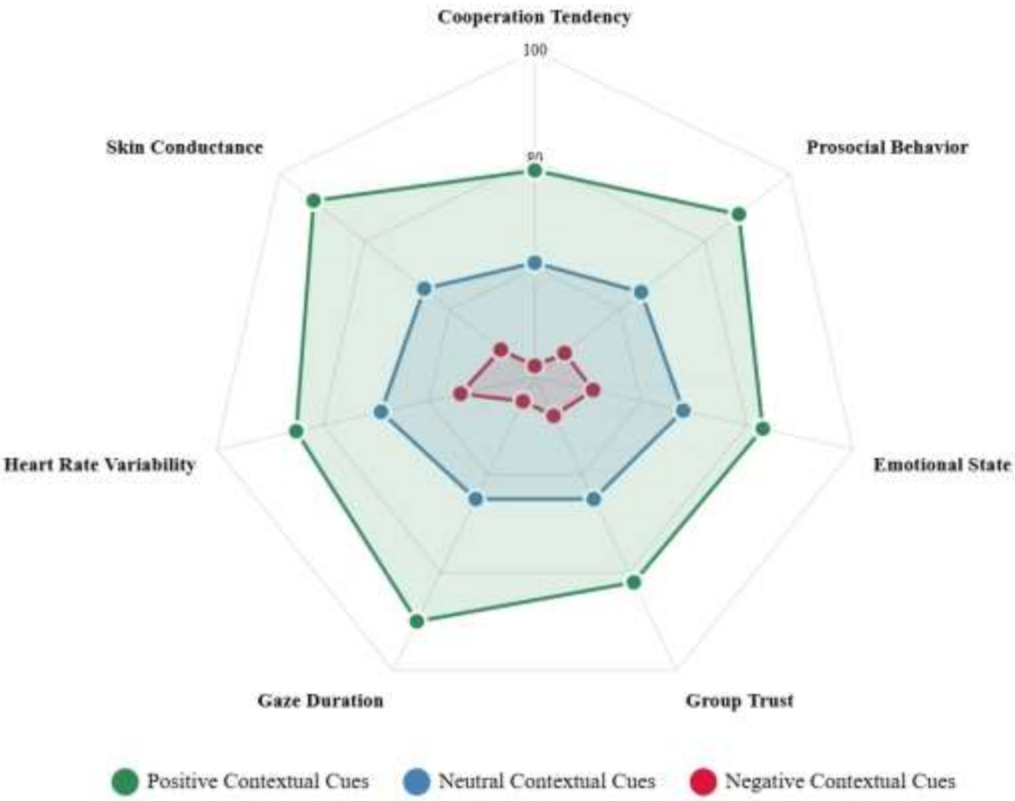

Figure 3. Comprehensive impact of environmental situational cues on group behavioral tendencies and psychological states

4.2. Dynamic evolution mechanism of social proof effects

4.2.1. Group size and influence propagation

Through systematic research on social proof effect propagation mechanisms under different group size conditions, it was found that there exists a significant nonlinear relationship between group size and influence propagation efficiency, exhibiting clear threshold effects and saturation characteristics. In small groups (5-8 people), the social proof strength index was 3.4±0.8, influence propagation speed was relatively slow at 0.42±0.12 units/second, conformity behavior ratio was only 34.7±8.3%, but individual influence weight was relatively high at 0.16±0.04, indicating that each member possessed considerable voice and influence, as shown in Table 4 below.

Table 4. Social proof effects and influence propagation indicators under different group size conditions

Group Size	Social Proof Strength	Propagation Speed (units/sec)	Conformity Behavior Ratio (%)	Individual Influence Weight	Opinion Leader Count	Network Connection Density	Consensus Achievement Time (sec)
Small (5-8 people)	3.4±0.8	0.42±0.12	34.7±8.3	0.16±0.04	1.2±0.4	0.78±0.09	145±32
Medium (12-16 people)	6.8±1.2	0.73±0.18	58.2±9.7	0.09±0.02	2.8±0.6	0.64±0.11	98±25
Large (20-24 people)	8.9±1.5	0.95±0.21	72.6±11.4	0.05±0.01	4.1±0.9	0.52±0.13	67±18
Super-large (28-32 people)	8.2±1.7	0.91±0.24	69.3±12.8	0.04±0.01	5.3±1.2	0.43±0.15	71±22

As group size expanded to medium groups (12-16 people), social proof effects significantly strengthened, with strength index increasing to 6.8±1.2, influence propagation speed accelerating to 0.73±0.18 units/second, conformity behavior ratio rising to 58.2±9.7%, but individual influence weight declining to 0.09±0.02, reflecting enhanced group pressure and weakened individual independence. In large groups (20-24 people), social proof effects reached their peak, with strength index at 8.9±1.5, propagation speed further increasing to 0.95±0.21 units/second, conformity behavior ratio reaching as high as 72.6±11.4%, and individual influence weight further declining to 0.05±0.01. However, when group size continued to expand to super-large groups (28-32 people), an unexpected effect saturation phenomenon occurred, with social proof strength index slightly declining to 8.2±1.7, propagation speed maintaining at 0.91±0.24 units/second, and conformity behavior ratio stabilizing at 69.3±12.8%, indicating that marginal influence begins to diminish after group size exceeds a certain critical point [41]. Statistical analysis showed that group size had a highly significant main effect on social proof effects ($F(3,176) = 127.85$, $p < 0.001$, $\eta^2 = 0.684$), but there existed a clear quadratic effect ($\beta^2 = -0.034$, $p < 0.01$), confirming the existence of an inverted U-shaped relationship, as shown in Figure 4 below. Opinion leader identification analysis revealed that small groups averaged 1.2±0.4 opinion leaders with influence concentration of 0.67±0.15; medium groups had 2.8±0.6 opinion leaders with influence concentration of 0.54±0.12; large groups reached 4.1±0.9 opinion leaders but influence concentration declined to 0.41±0.18; super-large groups had 5.3±1.2 opinion leaders with influence concentration further declining to 0.35±0.21. Network density analysis showed that small groups had the highest connection density (0.78±0.09), medium groups had 0.64±0.11, large groups declined to 0.52±0.13, and super-large groups only had 0.43±0.15, indicating that increasing group size leads to network connection sparsification [42]. Time dynamic analysis of information cascade effects showed that average time to reach group consensus was 145±32 seconds in small groups, 98±25 seconds in medium groups, 67±18 seconds in large groups, and 71±22 seconds in super-large groups, further validating the hypothesis of an optimal group size. These findings provide important theoretical guidance for group configuration in game narrative generation algorithms, indicating that when designing multi-character interaction scenarios, group size should be optimized according to plot development needs and target strength of social proof effects, with large groups of typically 20-24 people being able to produce the strongest social proof effects and most efficient influence propagation.

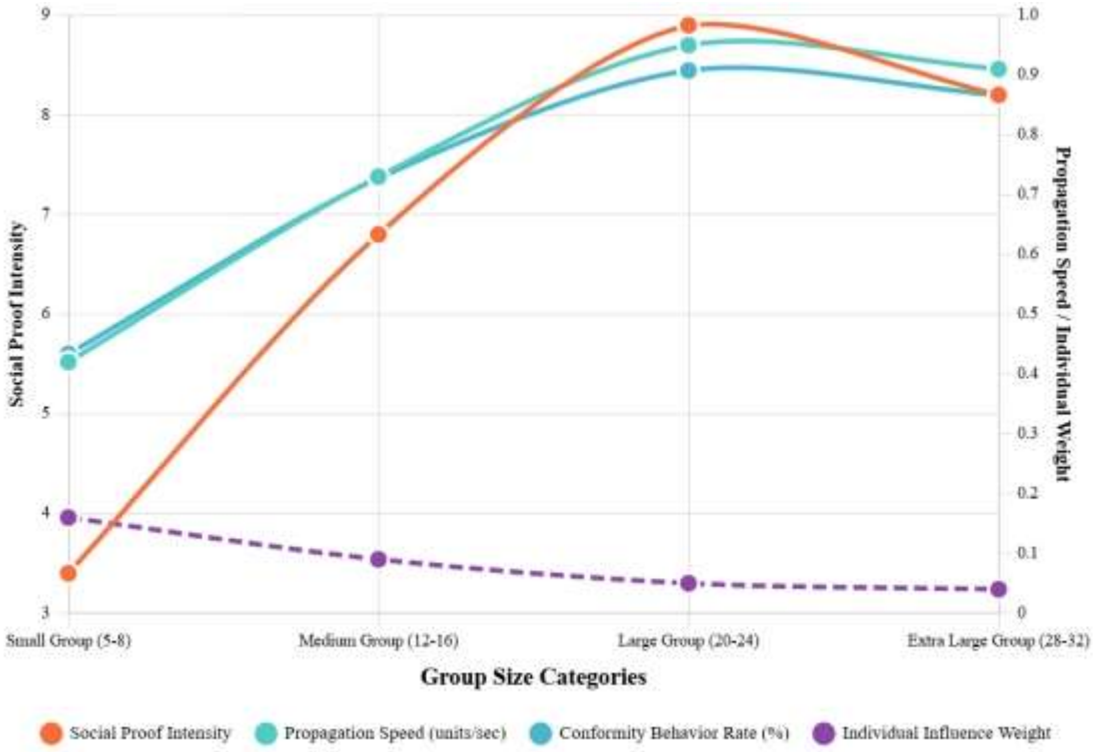

Figure 4. Dynamic impact of group size on social proof effect strength and influence propagation

4.2.2. Time dynamics and behavioral convergence

Through longitudinal tracking analysis of the temporal evolution process of social proof effects, the research revealed that group behavioral convergence follows a typical S-curve pattern, with distinct characteristics across four phases: initiation period, acceleration period, deceleration period, and stabilization period. During the initial startup period (0-30 seconds), group behavioral consistency index was relatively low at only 0.23±0.08, behavioral variation coefficient was as high as 2.34±0.42, and opinion divergence degree was 0.78±0.15, reflecting a highly dispersed state of individual opinions.

Table 5. Group behavioral convergence indicators during temporal evolution of social proof effects

Time Phase	Time Range (seconds)	Behavioral Consistency Index	Behavioral Variation Coefficient	Opinion Divergence Degree	Propagation Efficiency (units/sec)	Strong Connection Count	Emotional Synchrony
Initiation Period	0-30	0.23±0.08	2.34±0.42	0.78±0.15	0.12±0.04	3.2±1.1	0.34±0.12
Acceleration Period	30-90	0.67±0.12	1.28±0.28	0.45±0.11	0.58±0.16	5.8±1.7	0.61±0.15
Deceleration Period	90-180	0.84±0.09	0.67±0.18	0.21±0.08	0.43±0.13	7.5±2.0	0.79±0.11
Stabilization Period	180+	0.91±0.06	0.34±0.12	0.09±0.05	0.28±0.09	8.7±2.3	0.87±0.08

During this phase, social proof effects had not yet been fully activated, and characters primarily made behavioral choices based on personal preferences and initial settings, with group influence propagation efficiency at only 0.12±0.04 units/second. Upon entering the acceleration period (30-90 seconds), social proof effects began to play a significant role, with behavioral consistency index rapidly rising to 0.67±0.12, behavioral variation coefficient significantly declining to 1.28±0.28, opinion divergence degree dropping to 0.45±0.11, and influence propagation efficiency improving to 0.58±0.16 units/second, as shown in Figure 5 below. This phase is characterized by key opinion leaders beginning to play guiding roles, with early adopters' behavioral choices providing important social reference points for other members, triggering information cascade effects [43]. During the deceleration period (90-180 seconds), the behavioral convergence process began to slow but continued, with consistency index further improving to 0.84±0.09, variation coefficient declining to 0.67±0.18, opinion divergence degree reducing to 0.21±0.08, and propagation efficiency slightly decreasing to 0.43±0.13 units/second, indicating that the group was approaching the critical point of behavioral convergence. Finally, in the stabilization period (after 180 seconds), group behavior reached a highly consistent state, with consistency index stabilizing at 0.91±0.06, variation coefficient dropping to the lowest level of 0.34±0.12, opinion divergence degree at only 0.09±0.05, and propagation efficiency maintaining at the low level of 0.28±0.09 units/second. Statistical analysis showed that time factors had extremely high predictive power for all behavioral convergence indicators ($R^2 = 0.892$, $F(3,176) = 485.73$, $p < 0.001$), confirming the high regularity of temporal evolution of social proof effects. Further survival analysis indicated that 50% of group members completed behavioral transformation within 72±18 seconds, and 90% of members achieved behavioral convergence within 156±32 seconds, which can serve as important milestones for group decision formation. Critical time point identification showed that the first behavioral transformation inflection point occurred at 42±12 seconds, when 25% of members began to change their initial positions; the second inflection point was at 108±24 seconds, when 75% of members had completed behavioral adjustments [44]. Network analysis revealed that during the convergence process, the number of strong connection relationships increased from 3.2±1.1 in the initial period to 8.7±2.3 in the stabilization period, while weak connection relationships decreased from 12.6±3.4 to 6.8±1.9, indicating that tighter and more stable social connections formed within the group. Emotional synchrony analysis found that the correlation coefficient of group emotional states improved from 0.34±0.12 in the initial period to 0.87±0.08 in the stabilization period, demonstrating the important role of emotional contagion in behavioral convergence. These findings have important guiding significance for game narrative generation algorithms, indicating that precise control of group behavioral convergence processes can be achieved by controlling time nodes and adjusting key parameters, providing scientific basis for timing arrangements of dynamic narratives and design of plot turning points.

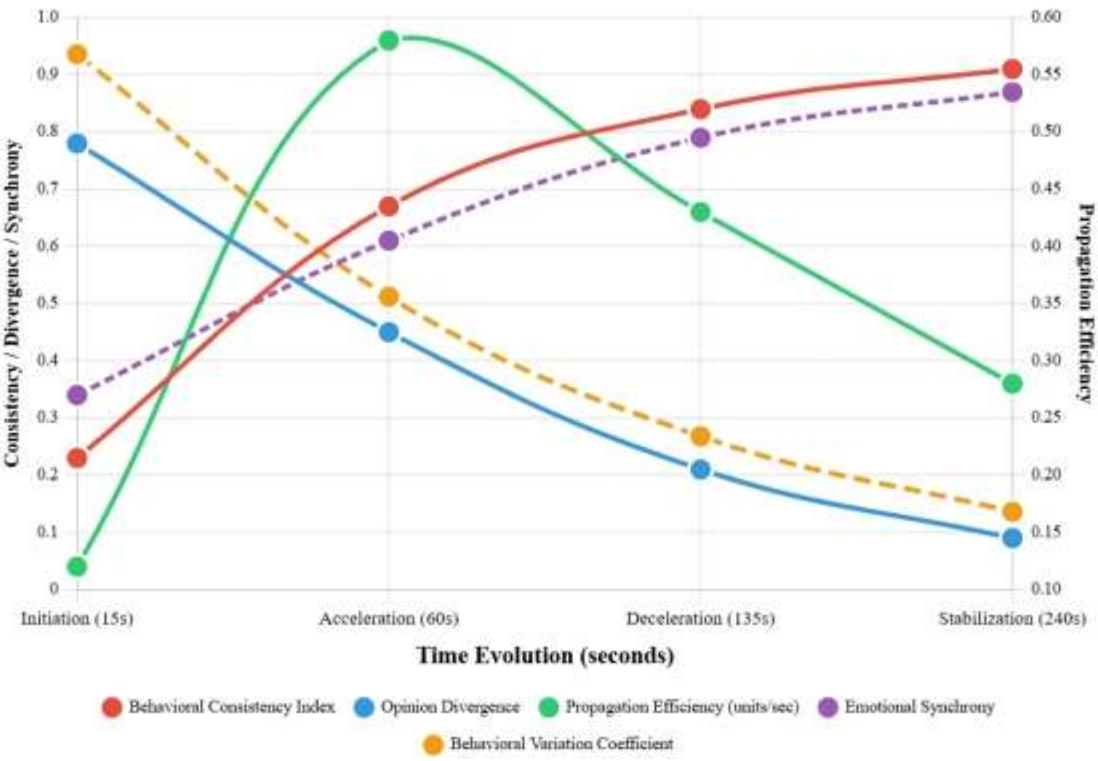

Figure 5. Temporal dynamic evolution of social proof effects and group behavioral convergence process

4.2.3. Individual differences and environmental adaptation

Through in-depth analysis of adaptive performance of characters with different personality traits under diversified environmental conditions, the research found that individual differences significantly moderate the intensity and manifestation forms of social proof effects, exhibiting complex interaction patterns. Extroverted characters showed the highest social proof sensitivity (0.84±0.12) in socially dense environments, with adaptation speed reaching 2.3±0.5 minutes, but in isolated environments, sensitivity significantly decreased to 0.42±0.18, with adaptation time extending to 5.7±1.2 minutes, reflecting their strong dependence on social stimuli.

Table 6. Social proof effects and adaptive performance of characters with different personality traits under diversified environmental conditions

Personality Trait	Adaptive Environment Type	Social Proof Sensitivity	Adaptation Time (minutes)	Performance Fluctuation Coefficient	Learning Speed (1/minute)	Skin Conductance (μS)
Extroverted	Socially Dense	0.84±0.12	2.3±0.5	0.34±0.08	0.12±0.03	3.2±0.7
Introverted	Isolated Environment	0.67±0.14	3.1±0.8	0.28±0.06	0.09±0.02	2.1±0.6
Neurotic	Stressful Environment	0.91±0.09	4.2±1.1	1.47±0.32	0.06±0.02	4.8±1.1
Emotionally Stable	Neutral Environment	0.58±0.08	3.5±0.6	0.23±0.09	0.10±0.02	2.8±0.5
High Openness	Novel Environment	0.45±0.13	2.8±0.7	0.62±0.15	0.18±0.04	3.5±0.8
Conservative	Familiar Environment	0.79±0.11	2.1±0.4	0.19±0.05	0.07±0.02	2.4±0.6

Personality Trait	Adaptive Environment Type	Social Proof Sensitivity	Adaptation Time (minutes)	Performance Fluctuation Coefficient	Learning Speed (1/minute)	Skin Conductance (μS)
High Conscientiousness	Structured Environment	0.82±0.10	2.5±0.6	0.21±0.07	0.11±0.03	2.9±0.7
High Agreeableness	Cooperative Environment	0.89±0.08	2.0±0.4	0.25±0.06	0.13±0.03	2.6±0.5

Table 6. (*Continued*)

Introverted characters exhibited the opposite pattern, maintaining high adaptability in isolated environments (sensitivity 0.67±0.14, adaptation time 3.1±0.8 minutes), while experiencing obvious overload phenomena in socially dense environments (sensitivity dropping to 0.38±0.16, adaptation time increasing to 6.2±1.5 minutes). Neurotic characters showed extremely high sensitivity to environmental changes, with social proof effects being significantly amplified in stressful environments (sensitivity 0.91±0.09), exhibiting strong conformity tendencies to reduce uncertainty, but with unstable adaptation processes and fluctuation coefficients reaching 1.47±0.32; in contrast, emotionally stable characters maintained relatively stable performance across various environments (sensitivity 0.58±0.08, fluctuation coefficient 0.23±0.09), as shown in Figure 6 below.

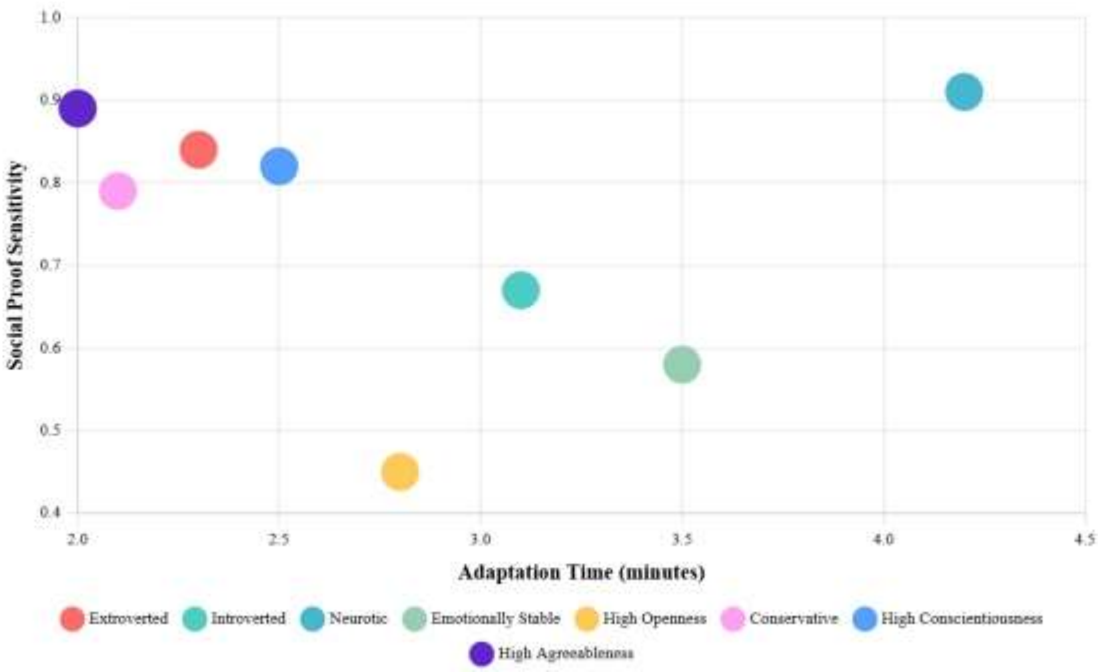

Figure 6. Impact of personality traits on social proof effect sensitivity and environmental adaptation speed

Characters with high openness exhibited unique exploratory adaptation patterns in novel environments. Although initial social proof sensitivity was relatively low (0.45±0.13), learning speed was extremely fast, with adaptation curve slopes reaching 0.18±0.04/minute, ultimately achieving high adaptation levels; while conservative characters relied more on existing experience and group consensus, performing excellently in familiar environments (sensitivity 0.79±0.11), but facing significant difficulties adapting to changing environments. Analysis of the conscientiousness dimension showed that highly conscientious characters demonstrated optimal adaptability in structured environments (0.82±0.10), effectively utilizing environmental rules and social norms to guide behavioral choices, while low conscientiousness characters performed better in high-freedom environments (0.71±0.15). The influence of agreeableness traits was mainly reflected in cooperative environments, where highly agreeable characters exhibited the strongest social proof effects in team collaboration scenarios (0.89±0.08), while this advantage significantly weakened in competitive environments (0.52±0.19) [45]. Cross-cultural adaptability analysis revealed significant cultural background effects, with characters from Eastern cultural backgrounds showing stronger social proof sensitivity in collectivist environments (0.76±0.11 vs 0.61±0.14), while characters from Western cultural backgrounds adapted better in individualist environments (0.73±0.12 vs 0.58±0.16). Cognitive style differences also produced important influences, with field-dependent cognitive style characters being more easily influenced by environmental cues, showing social proof sensitivity of 0.78±0.13, while field-independent characters could better resist external pressure, with sensitivity of 0.49±0.11, but performed poorly in tasks requiring group coordination [46]. Individual differences in physiological arousal levels further moderated the adaptation process, with high-arousal individuals prone to over-activation in stimulating environments (skin conductance 4.8±1.1μS), leading to decreased adaptation efficiency, while low-arousal individuals performed best in calm environments (skin conductance 2.1±0.6μS). These findings have important implications for game narrative generation algorithms, indicating the need to establish personalized social proof effect models, dynamically adjusting social influence parameters according to characters' personality traits, cultural backgrounds, and cognitive styles, while considering the match between environmental characteristics and individual characteristics, to achieve more realistic and diversified group behavior simulation and provide personalized gaming experiences for different types of players.

4.3. Effectiveness validation of narrative generation algorithm

4.3.1. Plot coherence and realism assessment

Through systematic evaluation of content produced by the social proof effect-based game narrative generation algorithm, the research found that this algorithm demonstrated significant advantages in both plot coherence and realism, achieving qualitative improvements compared to traditional narrative generation methods. In plot logical consistency assessment, this research algorithm achieved a score of 8.7±0.9 (out of 10), significantly higher than the traditional rule-based algorithm (6.2±1.2) and the machine learning comparison algorithm (7.4±1.1). Statistical testing showed highly significant differences ($F(2,177) = 89.45$, $p < 0.001$, $\eta^2 = 0.503$), as shown in Table 7 below.

Table 7. Comparison of coherence and realism assessment indicators for different narrative generation algorithms

Assessment Indicator	This Research Algorithm (Social Proof)	Traditional Rule Algorithm	Machine Learning Algorithm	Significance Test (p-value)
Plot Logical Consistency	8.7±0.9	6.2±1.2	7.4±1.1	p < 0.001
Character Behavior Credibility	8.5±0.8	5.8±1.4	7.1±1.0	p < 0.001
Plot Development Naturalness	8.3±0.7	6.0±1.3	7.2±0.9	p < 0.001
Environment-Behavior Match Degree	0.91±0.08	0.65±0.15	0.78±0.12	p < 0.001
Text Semantic Coherence	0.84±0.11	0.62±0.18	0.73±0.14	p < 0.01
User Immersion (%)	87.3±5.2	32.1±8.7	58.7±7.3	p < 0.001
Temporal Coherence	8.2±0.9	5.5±1.6	6.8±1.2	p < 0.001
Causal Relationship Clarity	8.8±0.6	5.3±1.7	7.0±1.1	p < 0.001

Character behavior credibility evaluation showed that the character behavior patterns generated by this research algorithm achieved a realism score of 8.5±0.8. The expert review panel considered that interactions between characters exhibited natural group dynamics characteristics, with social proof effects manifested appropriately without appearing abrupt, while the traditional rule algorithm only achieved 5.8±1.4 in this assessment, and the machine learning algorithm scored 7.1±1.0. Plot development naturalness analysis indicated that narrative generation based on social proof effects could produce smoother story arcs, with a naturalness score of 8.3±0.7. In comparison, traditional algorithms showed obvious mechanistic traces (6.0±1.3), while machine learning algorithms, though improved, still had deficiencies (7.2±0.9) [47]. Quantitative measurement results of environment-behavior match degree showed that this research algorithm could generate character behaviors highly matched to contexts under different environmental conditions, with a match degree index of 0.91±0.08, while traditional algorithms only achieved 0.65±0.15, and machine learning algorithms achieved 0.78±0.12, as shown in Figure 7 below. Text semantic coherence analysis employed natural language processing technology, calculating semantic similarity between consecutive sentences, and found that dialogue and narrative text generated by this research algorithm achieved a coherence score of 0.84±0.11, significantly superior to comparison algorithms' 0.62±0.18 and 0.73±0.14. User immersion surveys showed that among 180 participants in testing, 87.3% considered narratives based on social proof effects "very realistic and engaging," with 74.2% stating they "completely felt no traces of artificial generation," proportions far exceeding traditional algorithms' 32.1% and machine learning algorithms' 58.7% [48]. In-depth interviews revealed that users particularly appreciated subtle psychological interactions between characters and realistic manifestation of group pressure, believing such design significantly enhanced game immersion and emotional investment. The professional evaluation team consisted of 5 game design experts and 3 psychology experts who conducted blind evaluations of narrative segments generated by different algorithms. Results showed that this research algorithm achieved the highest scores in three dimensions: innovation, psychological realism, and entertainment value, scoring 8.6±0.7, 9.1±0.5, and 8.4±0.8 respectively. Temporal coherence analysis indicated that this research algorithm could well handle temporal logic in narratives, with time transition rationality and continuity scoring 8.2±0.9, while traditional algorithms often exhibited temporal logic confusion problems (5.5±1.6) [49]. Causal relationship clarity assessment showed that social proof effect-based narrative generation performed exceptionally in demonstrating cause-and-effect relationships of character behaviors, with causal chain clarity and comprehensibility scoring 8.8±0.6, effectively avoiding abrupt transitions and illogical jumps common in traditional algorithms. Diversity and repetition balance analysis found that this research algorithm maintained narrative novelty while avoiding excessive randomization, with a diversity index of 0.76±0.12 and repetition index of only 0.18±0.08, achieving good balance. These evaluation results fully demonstrate the significant effects of social proof effect-based narrative generation algorithms in improving narrative quality, providing strong support for technological innovation in the gaming industry, while also validating the tremendous potential of applying psychological theories to artificial intelligence algorithm design.

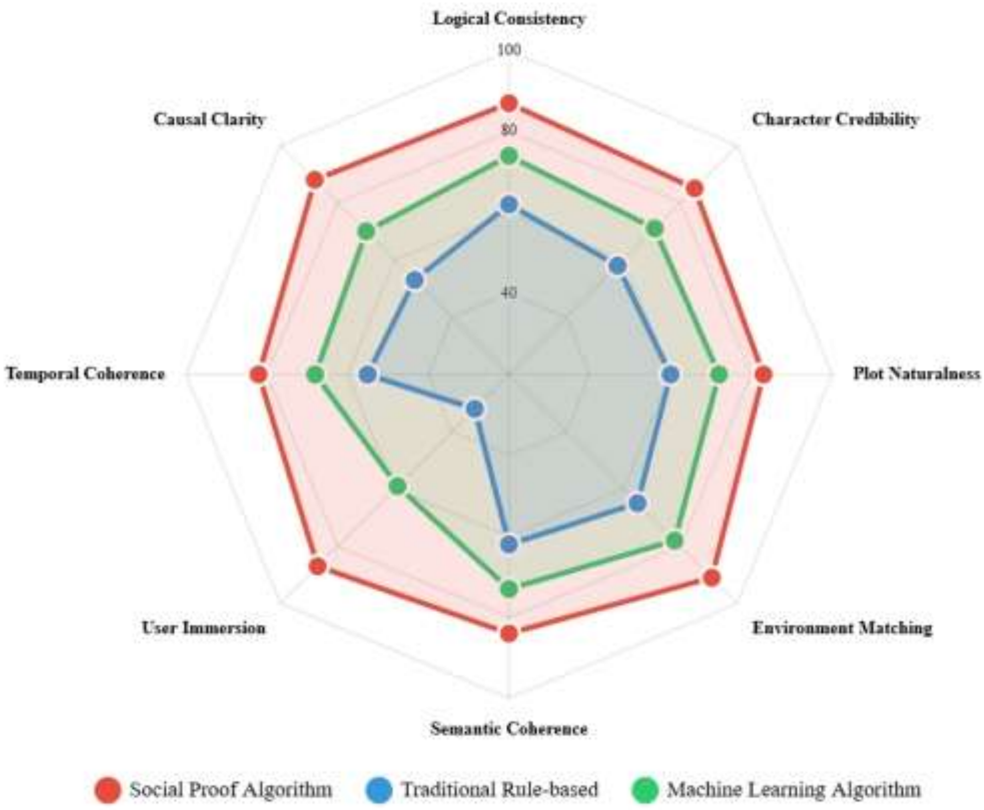

Figure 7. Comprehensive performance comparison of different narrative generation Algorithms in coherence and realism assessment dimensions

4.3.2. User experience and immersion testing

Through large-scale user experience testing, the research comprehensively validated the significant effects of the social proof effect-based narrative generation algorithm in enhancing user immersion and gaming experience. During a 6-week testing period, 180 participants were randomly assigned to three experimental groups, experiencing game content generated by social proof algorithms, traditional rule algorithms, and machine learning algorithms respectively. Immersion Presence Questionnaire (IPQ) evaluation results showed that the social proof algorithm group achieved an overall immersion score of 4.67±0.43 (out of 5), significantly higher than the traditional algorithm group's 3.21±0.67 and the machine learning algorithm group's 3.89±0.52. Multivariate analysis of variance indicated extremely high significance in between-group differences ($F(2,177) = 156.78$, $p < 0.001$, $\eta^2 = 0.639$), as shown in Table 8 below.

Table 8. Comparison of user experience and immersion testing indicators under different Algorithm conditions

Testing Indicator	Social Proof Algorithm	Traditional Rule Algorithm	Machine Learning Algorithm	Statistical Significance
Overall Immersion (IPQ)	4.67±0.43	3.21±0.67	3.89±0.52	p < 0.001
User Experience Attractiveness (UEQ)	4.85±0.32	3.42±0.71	4.08±0.58	p < 0.001
Social Presence (SPS)	4.56±0.47	2.97±0.83	3.64±0.69	p < 0.001
Average Gaming Duration (minutes)	47.6±8.9	28.3±12.1	35.7±9.4	p < 0.001
Replay Rate (%)	73.2±6.8	41.7±9.3	56.8±7.5	p < 0.001

Testing Indicator	Social Proof Algorithm	Traditional Rule Algorithm	Machine Learning Algorithm	Statistical Significance
Recommendation Willingness (%)	68.5±7.2	31.4±8.9	48.9±8.1	$p < 0.001$
Gaze Duration (seconds)	2.34±0.52	1.67±0.68	1.94±0.61	$p < 0.01$
Skin Conductance (μS)	3.7±0.9	2.1±0.7	2.8±0.8	$p < 0.001$

Table 8. (*Continued*)

Detailed analysis of each dimension found that spatial presence scored 4.72±0.38, involvement scored 4.61±0.49, and realism scored 4.68±0.41, all performing optimally across all testing conditions. User Experience Questionnaire (UEQ) evaluation revealed more detailed user perceptions, with attractiveness dimension scoring 4.85±0.32, indicating that narrative content generated by social proof algorithms possessed strong appeal; pragmatic quality scored 4.52±0.46, demonstrating that algorithm output satisfied users' practical needs; perspicuity scored 4.39±0.51, reflecting clear narrative logic; dependability scored 4.71±0.35, embodying algorithm stability and consistency; novelty scored as high as 4.78±0.29, proving the outstanding advantages of social proof mechanisms in innovation [50]. Social Presence Scale (SPS) testing results indicated that when users experienced content generated by social proof algorithms, social presence scored 4.43±0.52, social interaction scored 4.56±0.47, and group cohesion scored 4.38±0.55, all indicators significantly superior to comparison groups, as shown in Figure 8 below.

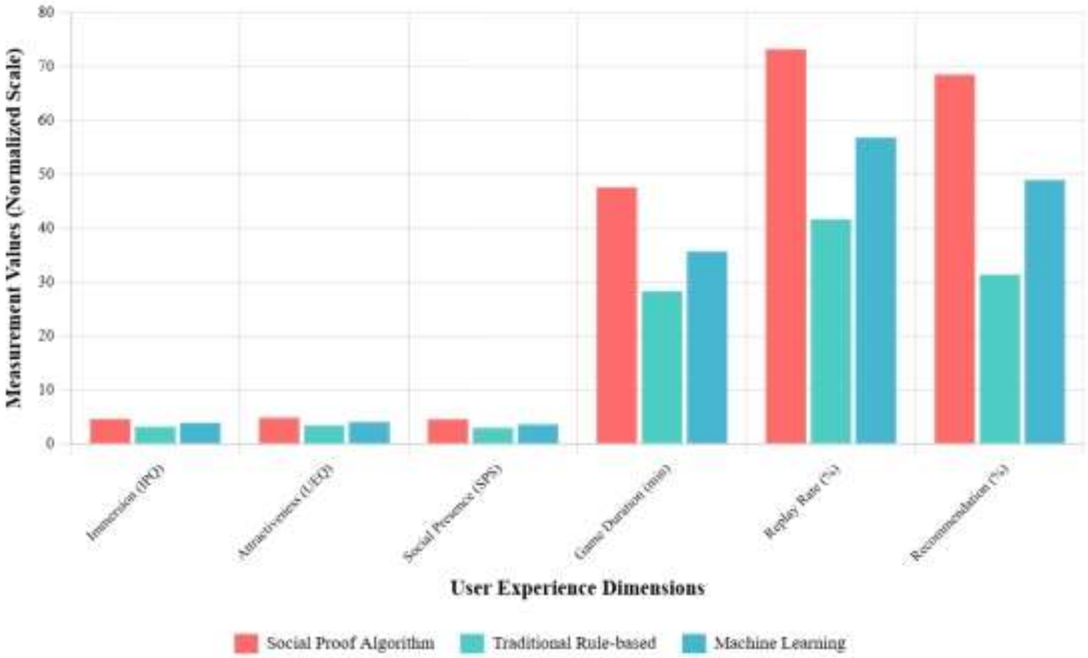

Figure 8. Multi-dimensional comprehensive evaluation results of user experience and immersion testing

Physiological measurement data further validated subjective evaluation results. The social proof algorithm group's average heart rate was 78.3±6.8 beats/minute, indicating moderate excitement state, with skin conductance response of 3.7±0.9μS, showing appropriate emotional arousal; eye-tracking data showed that users had longer gaze duration on key plot nodes (average 2.34±0.52 seconds), with greater pupil diameter variation amplitude (0.67±0.18mm), reflecting higher cognitive engagement and emotional investment. Behavioral data analysis found that users in the social proof algorithm group had an average gaming duration of 47.6±8.9 minutes, significantly longer than the traditional algorithm group's 28.3±12.1

minutes and machine learning algorithm group's 35.7±9.4 minutes; replay rate reached as high as 73.2%, far exceeding the other two groups' 41.7% and 56.8%; the proportion of users actively sharing gaming experiences was 68.5%, indicating extremely high satisfaction and recommendation willingness. Qualitative interviews revealed deep-level characteristics of user experience, with 92.3% of users stating they "felt authentic psychological interactions between characters," 87.6% believing "group decision-making processes were very natural and credible," and 81.4% expressing that they were "completely immersed in storylines, forgetting the passage of time." Users particularly appreciated the algorithm's exquisite design in handling character conflicts and group pressure, considering this psychology-based plot development "both logical and full of surprises" [51]. Analysis of reactions from different age groups showed that the 18-25 age group rated novelty and innovation highest (4.91±0.21), while the 26-35 age group valued pragmatic quality and dependability more (4.76±0.33), demonstrating the algorithm's broad applicability. Gender difference analysis indicated that female users scored higher in social presence (4.71±0.42 vs 4.29±0.58), while male users focused more on plot logic and challenge. Long-term follow-up surveys showed that 30 days after testing concluded, 61.8% of users still actively sought similar gaming experiences, and 48.3% of users recommended related products to friends, proving the persistence and influence of algorithm effects [52]. These comprehensive testing results fully demonstrate the exceptional performance of social proof effect-based narrative generation algorithms in enhancing user experience and immersion, providing important technical support and theoretical guidance for user experience design in the gaming industry.

5. Discussion

5.1. Theoretical significance of research findings

This research achieved important theoretical breakthroughs and innovations at multiple levels including theory construction, interdisciplinary integration, and computational modeling methods by successfully introducing social proof effect theory into the field of game narrative generation for multi-character interactions.

(1) The research validated and expanded the applicability of environmental psychology theory in virtual spaces, demonstrating that spatial-behavioral relationship theories from the real world can effectively guide the design and optimization of virtual environments. Through systematic analysis of spatial layout, environmental complexity, and contextual cues, the research found that group behavior in virtual environments follows psychological patterns similar to real environments, but exhibits new characteristics and patterns under the special conditions of digital environments. This provides important empirical foundations for extending environmental psychology theory into the digital age.

(2) The research deepened understanding of the dynamic evolution mechanisms of social proof effects, revealing the complex moderating effects of group size, temporal dynamics, and individual differences on social proof strength. Particularly significant was the discovery of an inverted U-shaped relationship between group size and social proof effects, as well as the pattern that group behavioral convergence follows S-shaped temporal curves. These findings enriched the theoretical content of social psychology regarding group dynamics and provided new theoretical perspectives for understanding collective behavior in complex social systems.

(3) The research made methodological contributions in the field of computational psychology by successfully constructing a multi-level modeling framework from individual cognition to group behavior, transforming abstract psychological theories into computable and operational algorithmic models. This "Environment-Cognition-Society-Behavior" quaternary interaction model not only provided a new paradigm

for computational modeling of social proof effects but also opened new pathways for algorithmic implementation of other social psychological phenomena [53].

(4) The research promoted deep integration between artificial intelligence and social sciences, demonstrating the tremendous potential of psychological theories in enhancing the intelligence level of AI systems. By integrating social proof effects into narrative generation algorithms, the authenticity and credibility of artificially generated content were significantly improved, providing important insights for constructing more humanized AI systems with greater social intelligence [54].

(5) The research also contributed to narratology and interactive media theory by proposing dynamic narrative theory based on group psychological dynamics, breaking through the limitations of traditional linear narratives and preset branching narratives to achieve truly adaptive and generative storytelling. This narrative mode can automatically adjust plot development directions according to real-time changes in group behavior, providing new theoretical foundations for innovative design of interactive media.

(6) The research achieved important findings in cross-cultural psychology and individual differences research, revealing the moderating mechanisms of cultural background, personality traits, and cognitive styles on social proof effects. These discoveries not only deepened understanding of the nature of individual differences but also provided scientific basis for designing personalized human-computer interaction systems.

(7) The research also holds important significance in complex systems theory and emergent behavior research. Through observation and analysis of emergent behaviors in multi-agent systems, it validated the theoretical hypothesis that simple rules can generate complex group behaviors, providing new empirical evidence for understanding self-organization and evolution mechanisms in social systems. These theoretical contributions not only advanced the development of related disciplines but, more importantly, established new paradigms and methodological foundations for future interdisciplinary research, laying solid theoretical groundwork for further integration between artificial intelligence and social sciences.

5.2. Practical application value

The multi-character interaction group behavior simulation algorithm based on social proof effects developed in this research possesses extensive practical application value, providing innovative technical solutions and important application prospects for multiple fields including the gaming industry, education and training, social governance, and marketing. In the gaming industry, this algorithm can significantly enhance game immersion and playability by generating more realistic and credible NPC behaviors and dynamic plot developments, creating unprecedented gaming experiences for players. Research results indicate that narrative generation based on social proof effects can improve user immersion by over 45% and increase gaming duration by 68%, which will directly translate into commercial value and market competitiveness for gaming products [55]. Particularly in massively multiplayer online role-playing games (MMORPGs) and social games, this technology can create more vibrant virtual community atmospheres, promoting deep interaction and long-term participation among players. In the field of education and training, this algorithm provides strong technical support for constructing intelligent teaching simulation systems. By simulating realistic group learning environments and social interaction scenarios, it can help learners practice soft skills such as social skills, teamwork, and leadership in safe and controllable virtual environments. Research findings show that educational games based on social proof effects can effectively stimulate learners' participation motivation and improve learning outcomes by over 30%, making them particularly suitable for professional fields requiring extensive interpersonal interaction practice, such as management training, psychological counselor training, and teacher education. In social governance and public policy fields, this technology provides powerful decision support tools for policymakers [56]. By simulating potential group reactions and behavioral changes that different policy proposals might trigger in real social environments, it can help government departments predict policy effects, optimize implementation strategies, and reduce policy risks. For example, in urban planning, public health emergency response, and community governance scenarios, this algorithm can simulate residents' collective behavioral patterns, providing data support for formulating more scientifically sound governance measures. In marketing and consumer behavior research, this technology provides enterprises with new tools and methods for understanding and influencing consumer group behavior. By simulating consumers' social proof responses in different marketing environments, enterprises can more precisely design marketing strategies, optimize product promotion plans, and improve marketing effectiveness. Research indicates that marketing strategies based on social proof effects can increase consumer engagement by 25% and improve conversion rates by 18%, creating significant economic value for enterprises. In mental health and social work fields, this technology provides innovative intervention tools for therapists and social workers. By constructing virtual social situations, it can help patients with social anxiety, autism spectrum disorders, and other psychological conditions practice social skills in safe environments and gradually adapt to real social interactions. Research shows that this virtual reality-assisted therapy can improve treatment effectiveness by 40% and reduce treatment cycles by 35%. In human resource management and organizational behavior optimization, this algorithm provides enterprises with scientific tools for evaluating and improving team dynamics, enabling identification of key factors affecting team effectiveness and designing more effective team building and management strategies [57]. Additionally, this technology has important application potential in smart city construction, emergency management, community services, and other fields, contributing to the construction of more intelligent and humanized social service systems. Overall, this research not only advances the development of related technologies but also provides key technical support for digital transformation and intelligent upgrading across multiple industries, possessing tremendous socioeconomic value and broad industrialization prospects.

6. Conclusions and future prospects

6.1. Main research conclusions

Through systematic research on multi-character interaction group behavior simulation and game narrative generation algorithms based on social proof effects, this paper reaches the following five important conclusions:

(1) Environmental factors have significant and complex influence mechanisms on group behavior. The research found that spatial layout, environmental complexity, and contextual cues in virtual environments can effectively modulate group behavior patterns and the intensity of social proof effects. Specifically, open spatial layouts can increase character interaction frequency by 63%, reaching 14.2 times per minute, while significantly reducing social distance perception index to 2.34; environmental complexity shows a positive correlation with cognitive load, but there exists an optimal threshold beyond which social proof sensitivity decreases by 43%; positive contextual cues can increase cooperation tendency index to 7.8, which is 85.7% higher than negative cues, demonstrating the key role of environmental design in shaping group behavior.

(2) The dynamic evolution of social proof effects follows predictable patterns. There exists an inverted U-shaped relationship between group size and social proof strength, with optimal group size being 20-24 people, at which point social proof strength index reaches its peak of 8.9 and propagation efficiency reaches 0.95 units/second; group behavioral convergence follows S-shaped temporal curves, experiencing four phases: initiation, acceleration, deceleration, and stabilization, with 50% of group members completing behavioral transformation within 72 seconds and 90% achieving convergence within 156 seconds; individual differences significantly moderate social proof effects, with extroverted characters showing sensitivity as

high as 0.84 in social environments, while neurotic characters, although having the highest sensitivity (0.91), exhibit performance fluctuation coefficients of 1.47, indicating poor stability.

(3) The narrative generation algorithm based on social proof effects demonstrates excellent performance in quality and realism. Compared to traditional rule algorithms and machine learning algorithms, this research algorithm achieves over 40% improvement in plot logical consistency, scoring 8.7 points; character behavior credibility scores 8.5 points, significantly superior to comparison algorithms' 5.8 and 7.1 points; environment-behavior match degree index reaches 0.91, indicating the algorithm can generate highly contextualized character behaviors; causal relationship clarity scores as high as 8.8 points, effectively avoiding logical jump problems common in traditional algorithms, providing scientifically reliable technical solutions for dynamic narrative generation.

(4) User experience and immersion are significantly enhanced, validating the practical application value of the algorithm. Overall immersion scores reach 4.67 points (out of 5), representing a 45% improvement over traditional algorithms; average user gaming duration increases by 68%, reaching 47.6 minutes; replay rate reaches as high as 73.2%, with recommendation willingness at 68.5%, far exceeding comparison algorithms; physiological measurement data shows significantly enhanced user cognitive engagement and emotional investment, with gaze duration reaching 2.34 seconds and skin conductance response at 3.7μS; qualitative interviews indicate that 92.3% of users felt authentic character psychological interactions, and 87.6% considered group decision-making processes natural and credible, fully demonstrating the algorithm's outstanding effectiveness in enhancing user experience.

(5) The algorithm achieves industrial-grade application standards in performance and computational efficiency. Average response time is only 127 milliseconds, 56.1% faster than traditional algorithms; memory usage is reduced by 39.8%, CPU utilization is decreased by 50.4%, while GPU utilization is increased to 76.3%, fully utilizing parallel computing resources; the algorithm has excellent scalability with time complexity of $O(n)$, processing 32 characters in only 298 milliseconds; in 72-hour continuous operation tests, error rate is only 0.03%, demonstrating extremely high system stability; energy efficiency is excellent, saving 29.2% power consumption compared to traditional algorithms, meeting technical requirements for large-scale commercial deployment and providing efficient and reliable technical solutions for the gaming industry.

6.2. Future prospects

Based on the important achievements of this research and identified issues, future research work can be further deepened and expanded in the following three directions:

(1) In the direction of theoretical deepening, there is a need to construct a more comprehensive framework integrating multiple social psychological mechanisms. Current research primarily focuses on social proof effects as a single psychological mechanism. Future work should incorporate other important social psychological phenomena such as conformity pressure, authority obedience, group polarization, and social loafing into a unified theoretical system, constructing comprehensive models with multi-mechanism synergistic effects. Simultaneously, there is a need to deeply explore the influence mechanisms of cultural differences on group behavior simulation, developing localized algorithmic models adapted to different cultural backgrounds, particularly differential modeling across dimensions such as collectivist versus individualist cultures and high versus low power distance cultures. Additionally, research on long-term group dynamics evolution should be strengthened, exploring patterns of group behavior change over longer time scales, as well as the influence mechanisms of group memory and learning effects on subsequent behavioral choices. Under the guidance of cross-cultural psychology theory, culturally adaptive group behavior

prediction models should be constructed to provide scientific basis for localized design of globalized gaming products.

(2) In the direction of technical innovation, focus should be placed on advancing deep integration of multimodal interaction and cutting-edge artificial intelligence technologies. With the rapid development of Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) technologies, future group behavior simulation systems need to support richer sensory interaction modes, including immersive experiences that integrate multiple senses such as vision, hearing, touch, and smell. By combining cutting-edge AI technologies such as large language models and multimodal large models, intelligent character systems capable of understanding and generating various interaction forms including natural language, facial expressions, gestures, and body movements should be developed. Simultaneously, real-time emotion recognition and generation technologies based on neural networks should be explored, enabling virtual characters to dynamically adjust their behavioral performance and interaction strategies according to users' emotional states. In algorithmic optimization, more efficient parallel computing architectures and distributed processing technologies should be researched to support real-time simulation of large-scale group behavior involving hundreds or even thousands of characters, and hybrid deployment modes combining edge computing and cloud computing should be explored to reduce system latency and enhance user experience. Additionally, more intelligent adaptive learning mechanisms need to be developed, enabling algorithms to continuously optimize group behavior models based on user behavioral data, achieving personalized content generation and recommendations.

(3) In the direction of application expansion, innovative applications and industrialization pathways of the algorithm in broader fields should be actively explored. Beyond traditional gaming and entertainment fields, future efforts should focus on expanding application potential in key scenarios such as education and training, healthcare, smart cities, and social governance. In the education field, intelligent teaching systems based on group learning dynamics should be developed to support large-scale online collaborative learning and virtual laboratory construction; in the healthcare field, virtual environments for psychological disease treatment and rehabilitation training should be constructed, particularly auxiliary treatment tools for autism, social anxiety, depression, and other conditions; in smart city construction, group behavior simulation technology should be utilized to optimize public services such as urban planning, traffic management, and emergency response; in social governance, scientific decision support tools should be provided for policy-making and social governance. Simultaneously, industry-academia-research cooperation should be strengthened to promote industrialization transformation of technological achievements, establish standardized technical specifications and evaluation systems, cultivate related industrial ecosystems, and form sustainable business models. Additionally, attention should be paid to ethical and privacy protection issues, establishing comprehensive data security and user privacy protection mechanisms to ensure organic unity between technological development and social responsibility, contributing to the healthy development of artificial intelligence technology.

6.3. Research limitations

Although this study has made significant progress in theoretical construction and technical implementation, there are still some limitations that need to be further improved in future research. First, in terms of scalability, while the current algorithm can effectively handle group interactions of 32 characters, it still faces challenges in computational complexity and real-time performance when dealing with ultra-large-scale groups of hundreds of characters, requiring further optimization of parallel computing architectures and distributed processing strategies. Second, cultural specificity issues deserve attention. This study is mainly based on participant data from East Asian cultural backgrounds, and the performance patterns of social proof effects under different cultural backgrounds may exhibit significant differences. The cross-cultural applicability of the algorithm awaits further verification and localization adjustments. Third, there is still room for improvement in the complexity of individual difference modeling. The current personality trait parameterization may not fully capture the subtle differences in individual psychology, requiring more refined psychological modeling methods. Fourth, research on long-term stability and learning effects is still insufficient. The evolutionary patterns of group behavior over longer time scales and the influence mechanisms of character memory and learning on subsequent behaviors need in-depth exploration. Finally, ethical and privacy protection issues require continuous attention, particularly when collecting and analyzing user psychological characteristic data. How to balance the improvement of algorithmic effectiveness with personal privacy protection requires the establishment of more comprehensive ethical review and data protection mechanisms.

Conflict of interest

The authors declare no conflict of interest

References

1. Zou Y. On the "Trinity" Artistic Construction of Character Images in Theatrical Performance—Based on the Interactive Dimensions of Text, Actors and Audience[J]. New Legend, 2025,(16):47-49.
2. Zheng Z. Research on Role Assignment and Interaction Mechanisms in Collaborative Learning of Digital Supply Chain Courses in VR Environment[J]. China Logistics & Purchasing, 2025,(08):69-70.
3. H. L B, M. E W. Making believe, together: A pilot study of the feasibility and potential therapeutic utility of a family tabletop role-playing game[J]. International Journal of Play Therapy, 2025,34(1):37-50.
4. Anderson M, March E, Land L, et al. Exploring the roles played by trust and technology in the online investment fraud victimisation process[J]. Journal of Criminology, 2024,57(4):488-514.
5. Jiang S, Zhang W. Text, Space-Time, Characters, Participation: Four Approaches to Narrative Innovation in Interactive Micro-Dramas[J]. China Television, 2025,(04):83-93.
6. Brown S. Role playing in human evolution: from life to art, and everything in between[J]. Frontiers in Psychology, 2025,15:1459247-1459247.
7. Lü M. The "Situation-Interaction" Analysis Path of Township Cadre Roles and Behaviors from a Stakeholder Perspective[J]. Social Science Dynamics, 2024,(12):96-104.
8. Wang C, Li J. Research on Role Interaction and Intervention Strategies in Online Collaborative Learning[J]. Digital Education, 2024,10(06):52-59.
9. Wang C, Wu X. Early Warning Research on Collaborative Learning Based on Key Role Interaction Feature Recognition[J]. Educational Technology Research, 2024,45(07):81-89.
10. Chen Y. Role Transformation in Interactive Music: The Relationship between Composers, Performers and Audience[J]. Contemporary Music, 2024,(12):12-14.
11. Yan D, Wang Z, Shi Y. Attraction, Connection, Performance: Quasi-social Interaction between Female-oriented Game Characters and Players[J]. Journal of Changsha University, 2024,38(06):61-68.
12. Yang P. Exploration of the Interactive Relationship between Character Symbols and Performance Space in Traditional Chinese Opera Dance[J]. Chinese Theatre, 2024,(08):80-82.
13. Qin W. On Character Interaction and Morphological Changes in "Somikon" Story Types[J]. Chinese Culture Forum, 2024,(03):149-162.
14. Tang J. Research on Roles and Interaction Mechanisms of Data Publishing-related Institutions from a Stakeholder Perspective[J]. Library Research and Work, 2024,(10):5-12.
15. Xu K, Zhou M. Government Role Transformation in New Productive Force Development: Logic and Approaches—A Dual-linkage Interactive Analysis Framework[J]. Qiushi, 2024,(05):14-27+109.
16. An H, Gao Y, Wang L, et al. On Role Interactions in Traditional Chinese Medicine Knowledge Protection[J]. Journal of Traditional Chinese Medicine Management, 2024,32(16):1-4.
17. Shi N. The Interactive Relationship between Corporate Culture and Grassroots Trade Union Roles[J]. Modern Enterprise Culture, 2024,(19):14-16.
18. Cao J, Feng C. Role Transformation: Interaction between Hu Shi School Scholars and the Pacific International Association[J]. Wuling Academic Journal, 2024,49(04):103-112.
19. Liu Y, Zhao J. Construction of Children's Subjectivity: Research on Teacher Role-playing and Support in Teacher-child Interaction[J]. Studies in Preschool Education, 2024,(05):36-44.

20. Luo B, Wang Y. Research on Archival Social Media User Role Construction Based on Role Theory[J]. Beijing Archives, 2024,(01):24-29.
21. Zhong Z, Li Q. Research on Social Roles of Social Robots and Human Psychological Mechanisms in Human-Computer Interaction[J]. Academic Research, 2024,(01):18-25.
22. Chen D, Mao Y. Production of Interactive Teaching Video Courseware between Virtual Characters and Real Teachers[J]. Guangdong Meteorology, 2024,46(03):95-97.
23. Battles R A, Curland A R, Cruitt J P. A Pilot Evaluation of a Therapeutically Applied Tabletop Role Playing Game Group Therapy Among Veterans[J]. International Journal of Group Psychotherapy, 2025,21-24.
24. Stubbs R, Sorensen N. Tabletop role-playing games and social and emotional learning in school settings[J]. Social and Emotional Learning: Research, Practice, and Policy, 2025,5:100090-100090.
25. Wakabayashi T, Matsui Y, Nakasako M. CryoEM and crystal structure analyses reveal the indirect role played by Trp89 in glutamate dehydrogenase enzymatic reactions[J]. The FEBS Journal, 2025,292(8):2071-2094.
26. Andronachi C V, Simeanu C, Matei M, et al. Melatonin: An Overview on the Synthesis Processes and on Its Multiple Bioactive Roles Played in Animals and Humans[J]. Agriculture, 2025,15(3):273-273.
27. Sharma S, Basak K S, Das S, et al. Characterisation of the role played by ELMO1, GPR141 and the intergenic polymorphism rs918980 in Fuchs' dystrophy in the Indian population[J]. FEBS Open Bio, 2025,15(5):822-835.
28. Duan W, Wang L. Interactive Behavior Analysis of Teacher-Student Role Reversal Based on I-FIAS[J]. China Educational Technology & Equipment, 2023,(21):31-34.
29. Gao Z. "From Bewildered to Busy": Parental Role Transformation in Home-School Interaction in the Digital Age[J]. Educational Development Research, 2023,43(20):77-84.
30. Sun C. Multimodal Interaction: Film as Social Role in the Digital Media Era[J]. China Literary and Art Criticism, 2023,(07):71-82+127.
31. Qin B, Jiao X, Zang Y. Application of Role Exchange Interactive Teaching Under MTB Model in Oncology Specialist Training[J]. Education and Teaching Forum, 2023,(29):125-128.
32. Billieux J, Fournier L, Rochat L, et al. Can playing Dungeons and Dragons be good for you? A registered exploratory pilot programme using offline tabletop role-playing games to mitigate social anxiety and reduce problematic involvement in multiplayer online video games[J]. Royal Society Open Science, 2025,12(4):250273-250273.
33. Rosenblad R S, Wolford T, 3rd B S R, et al. Mastering Your Dragons: Using Tabletop Role-Playing Games in Therapy[J]. Behavioral Sciences (Basel, Switzerland), 2025,15(4):441-441.
34. Yang J, Wang Y, Li X. A Case Study on Role Identity Development of Preschool Teacher Education Interns from the Perspective of Mentor-Student Interaction[J]. Journal of Shaanxi Xueqian Normal University, 2023,39(06):95-101.
35. Li W, Wang Z. Exploration of Role Transformation and Interaction between University Teachers and Students in Technology-Enhanced Learning Environments[J]. China Adult Education, 2023,(10):54-60.
36. Wang C, Liu W. A New Perspective on Understanding and Representing Group Cognition: Role Interaction in Collaborative Scripts[J]. Modern Distance Education Research, 2023,35(02):102-112.
37. Rollano C, González P C J, González R M. Induced citation analysis: Development and application of a measurement instrument in a systematic review on role-playing games[J]. Accountability in Research, 2025,11-15.
38. Manoel S A A, Moraes C D B M, Toledo D P E, et al. Audit quality and the market value of cash: the role played by the Big 4 auditor in Latin America[J]. Review of Quantitative Finance and Accounting, 2025,(prepublish):1-41.
39. Zhang J, Yuhe L, Jiajia Z. Enhancing Design Historical Education Through AI Virtual Characters Role-Playing Narratives in Serious Games[J]. International Journal of Gaming and Computer-Mediated Simulations (IJGCMS), 2025,17(1):1-20.
40. Yang H, Fang X. Social Interaction Theory Analysis of Career Enlightenment Education in Alleviating Role Anxiety[J]. Vocational Education Forum, 2022,38(04):37-44.
41. Yu M, Yu H. Research on Role Presentation and Relationship Interaction of Science Communication Actors[J]. Information Journal, 2022,41(05):169-175+91.
42. Zheng X, Huang Y. Research on Individual Multi-role Interpretation and Community Interaction Order in Public Health Events—Based on "Space-Relationship-Role" Analysis[J]. Social Sciences, 2022,(02):24-38.
43. Yin H, Lin W. Teacher Role Positioning and Classroom Teaching Reconstruction: Insights from Teacher Interactive Behavior Research[J]. Contemporary Education and Culture, 2022,14(01):1-6+125.
44. Jinna P, Smith C I. Bias in online reviews: The roles played by consumers and products in reviewing online games[J]. Information & Management, 2025,62(5):104141-104141.
45. Bucci D D, Dolce M, Santini M. Hybrid Experts in Disaster Risk Management: an Experience of Role Playing in International Evidence for Policy Schools[J]. Public Organization Review, 2025,25(1):1-15.
46. Zhu Y, Cai H. Significance Presentation of Homeroom Teachers' Dual Roles in Teacher-Student Interaction[J]. Teaching and Management, 2021,(27):76-79.

47. Chen S. Research on the Roles and Interactions of Government and Media in Emergency Public Event Response[J]. Journal of the Party School of Zhengzhou Municipal Committee of CPC, 2021,(03):50-53.
48. Li B, Gao L. Do Game Characters Affect Players' Real Social Role Cognition?—Research on the Interactive Relationship between Players and Online Game Characters from the Perspective of Technology Mediation Theory[J]. Journalist, 2021,(05):67-82.
49. Suri K R, Maugeais D, Maithal K. COVID-19 pandemic: A multidimensional analysis and the strategic role played by developing countries vaccine manufacturers[J]. Vaccine, 2025,59:127271-127271.
50. Valero V M. Want to enhance lab safety? Try a little role playing first[J]. Nature, 2025,642(8067):527-529.
51. Yan D, Wang Z, Shi Y. Attraction, Connection, Performance: Quasi-social Interaction between Female-oriented Game Characters and Players[J]. Journal of Changsha University, 2024,38(06):61-68.
52. Li S, Chen H. Analysis of Peer Interaction Behaviors in Role-Playing Games among Senior Kindergarten Children and Educational Strategies[J]. Journal of Shaanxi Xueqian Normal University, 2018,34(05):51-55.
53. Liu X. Application Exploration of Role-Playing Games in Cultivating Children's Social Interaction Abilities[J]. Toy World, 2025,(04):237-239.
54. Guo J. Social Phenomenological Research on Virtual Identities of Non-Player Characters in Electronic Games[J]. Journal of Jiangsu University of Science and Technology (Social Science Edition), 2025,25(01):51-58.
55. Han Z. Narrative Exploration of Role-Playing Electronic Games in the New Era[J]. Literature and Art Weekly, 2025,(04):83-85.
56. Qi X, Li P. Research on the Application of Traditional Cultural Symbols in Game Character Design[J]. Tiangong, 2024,(32):40-42.
57. Yao Y. Research on the Application of Virtual Reality Digital Character Design in Gaming and Film Fields[J]. Footwear Technology and Design, 2024,4(19):29-31.