Cross-layer Discourse Ripples: a Quantitative Case Study of AI-Romance Narratives in Social Media Communication

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Abstract: This study quantitatively analyzes the discourse ripple effect generated by cross-platform communication of human-machine romantic relationship-related topics across three heterogeneous social media platforms: Douban, Zhihu and Rednote, to address the insufficient explanatory power of the unidimensional attenuation hypothesis in traditional communication studies. Based on social distance theory, a three-layer discourse space model is constructed, dividing Douban, Zhihu and Rednote into the direct-interaction layer, near-interpersonal layer and far-interpersonal layer respectively. A total of 899 user comments related to human-machine romantic relationship topics are collected from the three platforms. Jieba Chinese word segmentation and stop word filtering are adopted for text preprocessing. A self-developed Cross-layer Discourse Ripple Index (CDRI) is constructed to quantitatively measure discourse differences between adjacent layers from three dimensions: semantic resonance, emotional attenuation and discourse mutation rate. The composite ripple index from Douban to Zhihu reaches 0.8927, indicating a strong ripple feature; the index drops to 0.3411 from Zhihu to Rednote, presenting a weak ripple feature. TF-IDF semantic similarity of all three layer pairs is lower than 2%. Emotional intensity is reversely amplified by approximately 121% from Douban to Zhihu, while attenuating by about 25% from Zhihu to Rednote. A total of 3,721 new concepts emerge from Douban to Zhihu, compared with merely 606 new concepts from Zhihu to Rednote. The cross-platform communication of human-machine romantic relationship topics is not a linear attenuation process, but a complex dynamic system integrating emotional resonance, knowledge reconstruction and semantic mutation. The near-interpersonal layer exerts significant emotional amplification and conceptual reconstruction effects on core discourse, thus serving as the key mediating node of ripple communication.

Keywords: Cross-layer Discourse Ripple Index; Human-Machine Romantic Relationship; Cross-platform Communication; Social Distance Theory; Sentiment Analysis

1. Introduction

The rapid advancement of generative artificial intelligence is reshaping individuals' emotional structures and intimate relationship practices in contemporary society. Human-AI Romantic Relationships, formed by users with anthropomorphic conversational agents such as Replika and ChatGPT, have evolved from a marginal cultural phenomenon to a widely visible public social issue.

This phenomenon not only subverts traditional cognitive frameworks of interpersonal intimacy, but also undergoes continuous discussion, reproduction and outward diffusion via social media platforms, forming a crucial research sample for observing discourse communication mechanisms in the digital era.

Existing research lays theoretical foundations for this study in three dimensions. First, theoretical and empirical studies on human-AI emotional relationships. The media equation theory proposed by Reeves and Nass states that humans naturally apply social rules of interpersonal interaction when engaging with media such as computers and televisions [1]. In Alone Together, Turkle further warns that technology creates an illusion of "companionship without friendship", reshaping modern people's expectations for intimacy [2]. Recent empirical studies targeting social chatbots like Replika prove that users can develop attachment emotions toward AI partners based on two antecedent variables: anthropomorphism and perceived AI authenticity [3]. Adopting social penetration theory as the framework, interview research by Skjuve et al. reveals that human-AI relationships evolve through three stages: superficial exploration, emotional investment and stable bonding [4]. Laestadius et al. identify role-playing emotional dependence and corresponding mental health risks arising from user interaction with Replika [5]. Domestic scholars have also conducted reflective research on this topic: Peng Pan systematically discusses the panorama and prospects of human-machine relationships under intelligent communication [6]; Zeng Yuguo and Cao Jing conduct field observations based on Douban's "Human-AI Romance" group, pointing out that "cyber lovers" reflect people's projection of ideal selves and ethical dilemmas of intimate relationships [7]. These studies provide direct basis for the topic selection of this paper.

Second, theoretical resources regarding cross-platform discourse communication and psychological distance. Construal Level Theory (CLT) holds that the abstraction level of people's cognition of events is positively correlated with psychological distance—variations in spatial, temporal, social and hypothetical distance systematically alter the abstraction level of discourse construction [8,9]. Bar-Anan et al. verify through implicit association tests that an automatic correlation exists between social distance and cognitive construal level [10]. This theory provides cognitive psychological evidence for categorizing Douban, Zhihu and Rednote as the direct-interaction layer, near-interpersonal layer and far-interpersonal layer respectively. In terms of discourse communication research, Dong Wenchang points out that emotional communication in the era of group communication has become a core landscape of mediatized society, calling for new research paradigms and approaches [11].

Third, methodological resources for computational text analysis. The systematic term weighting method (TF-IDF) proposed by Salton and Buckley remains the baseline tool for text similarity measurement [12]. Nevertheless, its lexical matching characteristic leads to systematic limitations in semantic comparison across communities and platforms.

In summary, existing literature has generated abundant insights into human-AI emotional relationships, discourse communication, psychological distance and computational text analysis, yet three research gaps remain. First, research on human-machine romantic relationship topics is dominated by qualitative analysis and single-platform research, lacking quantitative characterization of cross-platform communication dynamics. Second, traditional communication studies mostly adopt the linear attenuation hypothesis to explain discourse diffusion, failing to capture emotional amplification or conceptual reconstruction phenomena in intermediate layers. Third, single-dimensional semantic similarity measurement cannot fully reflect substantive connections

between cross-community discourses.

Based on the above research gaps, this paper puts forward the following research question: Can quantifiable "ripple effects" be generated during the cross-platform communication of human-machine romantic relationship topics across heterogeneous social media platforms? What patterns do these effects present in semantic, emotional and lexical dimensions? Accordingly, this paper innovatively constructs the Cross-layer Discourse Ripple Index (CDRI). Through multi-dimensional measurement of 899 comments collected from Douban, Zhihu and Rednote, this paper answers the research question and delivers a new methodological tool for cross-platform discourse research on human-AI emotional interaction.

2. Materials and Methods

2.1 Research Design

This study adopts a three-layer discourse space model to conduct quantitative analysis on cross-platform communication of human-machine romantic relationship topics. The division of the three-layer discourse space draws on social distance theory: social distance refers to individuals' subjective perception of relational proximity between themselves and event subjects. Distinctions between self and others, acquaintances and strangers, in-group and out-group members, and similar and dissimilar individuals reflect varying degrees of interpersonal social distance [8-10]. On this basis, Douban is defined as the direct-interaction layer (Layer 1), Zhihu as the near-interpersonal layer (Layer 2), and Rednote as the far-interpersonal layer (Layer 3). By measuring differences and correlations between discourse features of adjacent layers, a multi-dimensional measurement framework for ripple effects is established.

The three selected research cases all focus on human-machine romantic relationships, with female core interactors, yet differ in layer positioning, presentation of emotional dilemmas and initiative of relationship breakdown. Case 1 (Douban) originates from a post within Douban's interest community discussing how AI amplifies self-perception. Commenters share personal interaction experiences with AI, expressing empathy and vigilance toward this phenomenon, representing the individual cognitive dimension of the direct-interaction layer. Case 2 (Zhihu) is a Q&A post asking "What should I do if my girlfriend breaks up with me for falling in love with AI?" Respondents offer sympathy, support, criticism and judgment for the male poster, representing the intimate relationship dimension of the near-interpersonal layer. Case 3 (Rednote) is an interview program themed on technology and emotional relationships, where a professor of technology philosophy interviews multiple women who have built intimate bonds with AI, discussing modern individuals' alienation and rejection of real interpersonal intimacy, representing the social attitude dimension of the far-interpersonal layer.

The core research logic is as follows: if core discourse produces a ripple effect, its semantic content, emotional intensity and expression form will undergo systematic changes as discourse spreads from inner layers to outer layers. Such changes are non-random and follow predictable patterns. Quantifying these variations not only verifies the existence of ripple effects, but also measures their intensity, direction and characteristics. The three cases reflect differentiated impacts of AI intervention on human emotional structures from individual cognitive, intimate relationship and social attitude dimensions, jointly outlining a complete picture of human-AI emotional interaction.

2.2 Data Source and Preprocessing

Research data consist of user comments collected from three social media platforms: Douban, Zhihu and Rednote. Specifically, 433 comments are extracted from Douban, 230 from Zhihu and 236 from Rednote, totaling 899 valid comment samples. The three platforms differ drastically in user relational structures, interaction modes and discourse styles: Douban is built on interest-based communities where users maintain direct interactive relationships; Zhihu operates as a knowledge Q&A community where users conduct in-depth discussions via long-form answers, forming semi-acquaintance networks; Rednote relies on visual content and stranger socialization, with discourse diffusion characterized by long-distance weak ties. Such platform heterogeneity forms a natural experimental field for observing discourse ripple effects.

Data preprocessing includes three steps. First, text cleaning: remove URLs, @user tags, special symbols and numeric characters, retaining only Chinese text content. Second, Chinese word segmentation: apply the jieba segmentation tool to split each comment into lexical units. Third, stop word filtering: construct a stop word list containing 127 common Chinese function words (e.g., de, le, zai) and single-character words with semantic insignificance, ensuring subsequent analysis focuses on semantically meaningful vocabulary. After preprocessing, each comment is converted into a token sequence and cleaned text string, laying a foundation for vectorization and similarity calculation. Figures 1 to 3 present word clouds for three cases, with typical terms translated.

2.3 Algorithm Design: Cross-layer Discourse Ripple Index (CDRI)

The Cross-layer Discourse Ripple Index comprises three dimensions: Semantic Resonance (SR), Emotional Attenuation (EA), and Discourse Mutation Rate (DMR), corresponding to three core facets of discourse communication: meaning transmission, emotional diffusion and formal variation.

Semantic Resonance measures the thematic similarity of discourse between adjacent layers. Calculation steps are as follows: all texts are combined for TF-IDF vectorization [12], with a maximum feature vocabulary count of 5000 and ngram_range=(1,2) to capture phrase-level semantic information. A cosine similarity matrix of text vectors from two layers is computed, and the average value is taken as the semantic resonance of the layer pair. Cosine similarity ranges from 0 to 1; values closer to 1 indicate stronger semantic resonance between layers. This indicator reflects the "fidelity" of core discourse during cross-layer diffusion, i.e., the degree to which original core meanings are preserved in outer layers.

Emotional Attenuation measures the rate of change in emotional intensity as discourse spreads across layers. This research constructs a simplified emotional lexicon containing 33 positive emotional words and 33 negative emotional words. For each comment, the sentiment score is calculated as (number of positive words − number of negative words) / (number of positive words + number of negative words), ranging from −1 to 1. The average absolute value of sentiment scores of all comments within a layer is defined as the emotional intensity of that layer. The formula for emotional attenuation is (Inner Layer Emotional Intensity − Outer Layer Emotional Intensity) / Inner Layer Emotional Intensity. Values below 0 signify emotional amplification during communication; values equal to 0 represent unchanged emotional intensity; values above 0 indicate emotional attenuation. This indicator reveals the dissipation or enhancement mechanism of emotional energy in discourse diffusion.

Discourse Mutation Rate measures the innovation and variation degree of discourse during communication. First, the Type-Token Ratio (TTR) of each layer is calculated as unique word count divided by total word count, eliminating interference from text length differences. Unique lexical

concepts of the outer layer (vocabulary appearing in the outer layer but absent in the inner layer) are then identified. The discourse mutation rate is defined as the count of unique new concepts / (total unique words of outer layer + 1), ranging from 0 to 1. Higher values represent greater discourse variation. This indicator reflects the "re-creation capacity" of different discourse communities when receiving core discourse, serving as a critical metric for understanding meaning reconstruction in cross-layer communication.

The composite ripple index formula is defined as: $CRI = \alpha \cdot SR + \beta \cdot (1-EA) + \gamma \cdot DMR$. This paper sets default weights α=0.4, β=0.3, γ=0.3. The weight allocation is theoretically grounded: meaning transmission constitutes the core of discourse communication, hence semantic resonance carries the highest weight; emotion acts as a driving force for discourse diffusion yet is not the sole determinant, assigned a medium weight; discourse variation embodies discourse vitality and adaptability, yet excessive variation may deviate from core meanings, also assigned a medium weight. Based on CRI values, ripple effects are categorized into three types: strong ripple (CRI>0.7), medium ripple ($0.4 \leqslant CRI \leqslant 0.7$), weak ripple ($CRI \leqslant 0.4$).

3. Results

Analysis of comment data from the three platforms yields the following results: the composite ripple index from Douban to Zhihu is 0.8927, the index from Zhihu to Rednote is 0.3411, and the cross-layer composite index from Douban to Rednote reaches 0.6106. Figure 1 visualizes this mutual influence relationship.

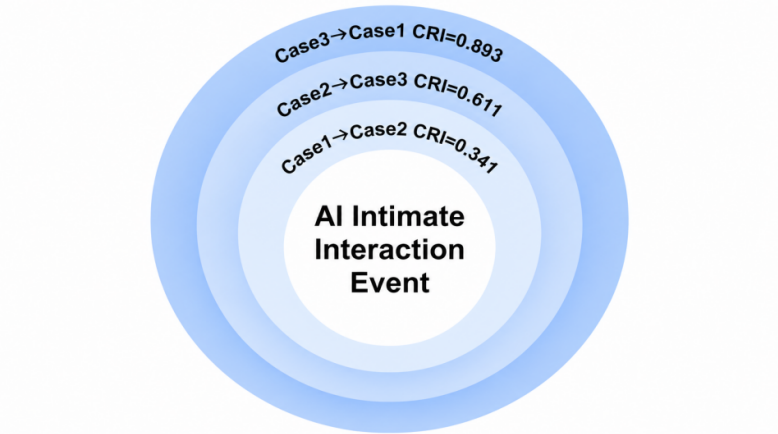


Figure 1: Concentric Ripple Model of Discourse Propagation

In terms of semantic resonance, the average similarity from Douban to Zhihu is 0.0147, 0.0155 from Zhihu to Rednote, and 0.0090 from Douban to Rednote; semantic similarity of all three layer pairs remains below 2%. Emotional retention reaches 2.2113 from Douban to Zhihu, 0.7489 from Zhihu to Rednote, and 1.6561 from Douban to Rednote. Discourse mutation rate is 0.7446 from Douban to Zhihu, 0.3673 from Zhihu to Rednote, and 0.3673 from Douban to Rednote.

In terms of emotional intensity: Douban's emotional intensity is 0.1496, with positive comments accounting for 11.64% and negative comments 3.33%; Zhihu's emotional intensity is 0.3309, with positive comments at 31.42% and negative comments at 4.87%; Rednote's emotional intensity is 0.2478, with positive comments accounting for 20.94% and negative comments 4.19%. In terms of lexical diversity: Douban's TTR is 0.3395, with total word count 6,857 and unique vocabulary 2,328; Zhihu's

TTR is 0.2987, total word count 16,725 and unique vocabulary 4,996; Rednote's TTR is 0.4078, total word count 4,044 and unique vocabulary 1,649. For unique emerging concepts: 3,721 new concepts emerge from Douban to Zhihu, while only 606 new concepts emerge from Zhihu to Rednote.

4. Discussion

Research results reveal three core theoretically significant findings that supplement and challenge traditional communication studies.

First, the anomalous emotional amplification phenomenon. Data show emotional retention from Douban to Zhihu reaches 2.2113, indicating emotional intensity is amplified by approximately 121% rather than attenuated during discourse diffusion from Douban to Zhihu. This finding challenges the traditional "distance attenuation" hypothesis in communication studies. Conventional theories argue that discourse influence gradually weakens during diffusion due to information loss and noise interference. However, this study confirms the existence of an "emotional resonance peak" under specific conditions: discourse generates stronger emotional resonance in an intermediate layer than the source layer. This phenomenon echoes Dong Wenchang's research on emotional communication in group communication media [11]: as a knowledge community, Zhihu users tend to conduct in-depth emotional investment and value judgment on topics, upgrading instant personal feelings from Douban into systematic emotional stance expressions, resulting in emotional amplification instead of attenuation. This aligns with Peng Lan's judgment that human-machine relationship topics under intelligent communication easily trigger in-depth value discussions [6].

Second, discourse variation follows a "knowledge reconstruction" pattern. The discourse mutation rate from Douban to Zhihu is 0.7446, accompanied by 3,721 emerging new concepts; the mutation rate drops to 0.3673 from Zhihu to Rednote, with merely 606 new concepts generated. Further frequency analysis of unique vocabulary shows high-frequency new concepts from Douban to Zhihu include "poster" (35 occurrences), "girlfriend" (32 occurrences), "love" (24 occurrences), "virtual" (23 occurrences), "interaction" (14 occurrences), reflecting the transformation from specific situational descriptions to abstract conceptual knowledge. In contrast, high-frequency new concepts from Zhihu to Rednote consist of character labels and emotional healing vocabulary such as "teacher" (33 occurrences), "host" (8 occurrences), "young lady" (4 occurrences), "healing" (4 occurrences). This staged characteristic from knowledge reconstruction to popular dissemination partially matches Construal Level Theory's prediction that psychological distance correlates positively with cognitive abstraction [9], yet this study further proves that abstraction is non-linear: discourse first undergoes intensive conceptualization (knowledge reconstruction) in the near-interpersonal layer, then downgrades to concrete character and situational labels when spreading to the far-interpersonal layer. This aligns with Zeng Yuguo and Cao Jing's field observation of Douban's human-AI romance community: when subcultural discourse spreads to broader communities, emotional symbols shift from abstract concepts to concrete reconstructed images [7].

Third, the "low similarity paradox" of semantic resonance. Semantic similarity of all three layer pairs stays below 2% (0.0147 for Douban→Zhihu, 0.0155 for Zhihu→Rednote, 0.0090 for Douban→Rednote), yet the composite ripple index of Douban→Zhihu reaches 0.8927, qualifying as a strong ripple effect. Superficially, extremely low semantic similarity suggests weak discourse correlation between layers. In-depth analysis explains this paradox: discourse inevitably shifts expression styles and lexical habits when transferring between different discourse communities, while core topics and emotional stances remain consistent. The TF-IDF method relies on lexical matching [12], failing to

capture deep semantic connections and thus severely underestimating actual semantic resonance. The CDRI algorithm proposed in this paper compensates for limitations of single semantic similarity indicators by incorporating emotional retention and discourse mutation rate, delivering a comprehensive portrait of cross-platform discourse communication. This discovery carries methodological significance: cross-platform discourse research relying solely on semantic similarity will underestimate discourse diffusion influence; integration of emotional dynamics and lexical variation analysis is mandatory for holistic research.

From a macro perspective, this study's findings echo core concerns of human-AI emotional relationship research. Turkle's warning of the "robot moment" [2], Pentina et al.'s empirical research on attachment formation with Replika [3], Skjuve et al.'s revelation of human-AI relationship developmental stages [4], and Laestadius et al.'s identification of mental health risks from emotional dependence [5] collectively demonstrate that human-machine romantic relationships are not merely individual psychological phenomena, but a continuously amplified and reshaped social landscape spread via social media networks. The media equation logic elaborated by Reeves and Nass [1] is further strengthened in the generative AI era, expanding into social cognitive changes through cross-platform discourse ripples.

This study admits several limitations. First, the three selected cases are typical rather than representative, failing to cover all discourse contexts of human-machine romantic relationships. Second, TF-IDF and simplified emotional lexicons are baseline analytical methods; future research can adopt pre-trained language models and fine-grained sentiment analysis for optimization. Third, although CDRI weight allocation is theoretically grounded, further empirical verification across diverse topics and platforms is required for calibration.

5. Conclusion

By constructing the Cross-layer Discourse Ripple Index (CDRI), this paper conducts multi-dimensional quantitative analysis on communication of human-machine romantic relationship topics across Douban, Zhihu and Rednote, drawing three core conclusions as follows:

First, cross-platform communication of human-machine romantic relationship topics presents a non-linear attenuating ripple effect pattern. Discourse spreading from Douban (direct-interaction layer) to Zhihu (near-interpersonal layer) generates a strong ripple effect (CRI=0.8927), while diffusion from Zhihu to Rednote (far-interpersonal layer) downgrades to a weak ripple effect (CRI=0.3411). The overall trend conforms to distance attenuation theory yet exhibits non-linear decay rates, accompanied by anomalous emotional amplification and conceptual reconstruction in inner layers.

Second, the near-interpersonal layer acts as the critical mediating node of ripple communication. Knowledge communities (Zhihu) demonstrate prominent emotional amplification (approximately 121%) and intensive conceptual reconstruction (3,721 new concepts) when receiving core discourse from interest communities (Douban). Further diffusion to lifestyle social platforms (Rednote) leads to emotional attenuation and reduced discourse variation. This pattern provides a new perspective for understanding discourse dynamics across heterogeneous platforms.

Third, as a multi-dimensional comprehensive measurement framework, CDRI effectively remedies defects of single semantic similarity indicators and delivers a new methodological tool for cross-platform discourse research. This framework can be generalized to study communication of other social topics across heterogeneous platforms. Especially under the discourse transformation

driven by generative AI, CDRI uniquely identifies emotional resonance peaks, knowledge reconstruction nodes and semantic variation paths. Future research can integrate fine-grained sentiment models and semantic embedding methods, expand research to more topics and platforms, and further revise and improve the proposed theoretical and methodological framework.

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