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Discussing Social Media Addiction from the Perspective of Educational Psychology Based on Student User Relationships

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Abstract Individuals who experience a fear of missing out (FoMO) often rely on social media as a means to alleviate their anxiety. Self-control, defined as the ability to regulate and manage one's behavior according to situational demands, plays a critical role in overcoming cognitive and emotional challenges. This study examines the moderating effect of self-control on the relationship between FoMO and social media addiction, highlighting how self-control can mitigate the negative psychological impacts of excessive social media use. Building upon the Improved Singular Value Decomposition (SVD) algorithm, the research investigates the underlying mechanisms linking FoMO to social media dependency and proposes an optimized model for achieving behavioral restraint. The findings underscore the potential of the enhanced SVD algorithm not only to deepen the understanding of FoMO–addiction dynamics but also to contribute to the development of strategies aimed at improving the social and psychological environment of digital platforms.

Index Terms social psychology, social media addiction, SVD collaborative filtering, algorithm optimization

I. Introduction

In real life, when the psychological needs of individuals are difficult to meet, they tend to seek spiritual satisfaction through social media applications. People with a strong sense of missing out often worry that they will miss important information or activities related to others, and social media serves as a medium for individuals to obtain information from the outside world. With the help of social media, people can not only know the whereabouts of others but also access the latest news and the scope of friends' group activities, thereby gaining a certain degree of psychological satisfaction.

Looking back at the promulgation and content of China's social media supervision policy from 2000 to 2020, it can be roughly divided into four stages: from 2000 to 2004, the issuance of social media policy was in the exploratory stage; from 2005 to 2007, the social media supervision policy entered a developmental phase; from 2008 to 2011, regulatory policies reached a peak period; from 2012 to 2014, the growth of regulatory policies gradually eased and stabilized; and from 2015 to 2020, regulatory policies entered another period of rapid growth. Although the number of social media supervision policies has increased year by year, the relatively narrow starting point of these policies has affected their overall effectiveness.

Scholars believe that the effectiveness of social media supervision policies is limited by the initial perspective of policy formulation. Most policies are developed with social media viewed primarily as a commodity, attempting to restrict social media behavior from a simple legal standpoint. The main purpose of analyzing social media interactive communication from the perspective of social psychology is threefold: first, to clarify the socialization characteristics of social media interactions; second, to analyze and explain the social motivations driving individuals to use social media; and third, to interpret individuals' cognition, emotion, and behavior in interpersonal and intergroup interactions through social psychology theory.

This paper explores the social psychology of both senders and receivers in social media interactions, focusing on the interplay of individual motivation and cognition, interpersonal interaction, and intergroup behavior. From this perspective, it analyzes and summarizes the cognitive motivations and behavioral patterns of social media participants, enabling individuals to better understand the communication environment and rules of interaction.

Social media has evolved from initial peer-to-peer emails to multi-dimensional platforms that reflect individual identity. This transformation has facilitated the shift from offline real-world relationships to online user nodes. As a new form of online social networking, social media not only promotes interpersonal communication but also enables people to find others with similar interests and hobbies, turning strangers into friends through shared activities. Platforms such as Weibo and WeChat demonstrate how social psychology can be applied to analyze interaction behaviors, helping users connect with like-minded individuals.

Identity crises and escapism often drive users to engage with social media, while social identity and virtual satisfaction serve as pull factors. Academic challenges, financial difficulties, limited personal opportunities, and dissatisfaction with life can contribute to individual confusion, leading to identity crises and prompting the search for refuge in social media. Additional contributing factors include a lack of family cultural capital, changes in family upbringing, and the stigmatization of vocational education, all of which encourage users to escape from real-life challenges.

The academic community also examines user relationships in the context of social media addiction. Studies address how changes in technology and platform design influence user interactions, including mobile social media experiences, social value, and digital labor practices. Research delves into the degree of correlation between user relationships and interest similarities, particularly in the context of social media recommender systems.

This paper first outlines the related concepts and research status of user relationships in social media. It then describes the current challenges in recommender systems for social media. To address these challenges, two functions are proposed to measure the similarity of user interests, and corresponding social regularization techniques are designed based on these functions. These are integrated into the SVD model. Finally, to verify the effectiveness of the proposed model, a suitable dataset is selected, and the results are compared with a classical matrix factorization-based social recommendation algorithm.

The issue of social media addiction has increasingly moved to the center of public discourse. Users are inevitably exposed to related information through media reports and other channels. As a thriving economic sector, social media plays a significant role in economic development but is also criticized as a “mental opium” that harms users. The debate around this topic persists. Understanding users’ risk perception of social media addiction from a social psychology perspective is essential for effectively delivering persuasive information and constitutes a key area of academic research.

II. Optimization of SVD Collaborative Filtering Algorithm Based on Student User Relationship Network

II. A. Introducing an Explicit Relational Network into the SVD Collaborative Filtering Algorithm

The main idea of the collaborative filtering algorithm using SVD decomposition, along with its corresponding loss function and solution, will serve as the basis for introducing an explicit relational network into the regularized SVD model. For clarity, this section reconsiders the potential of the regularized latent factor model. First, the definition of each variable in the recommendation algorithm is provided. Then, with the help of the latent factor model, the user rating can be expressed as follows:

$$r_{ui} = \theta_{ui} + \varepsilon_{ui} = p_u^T q_i + \varepsilon_{ui}, \tag{1}$$

where r_{ui} represents the rating of user u on item i, θ_{ui} is the predicted rating, and ε_{ui} is the prediction error.

In order to obtain these latent vectors, the regularized SVD method can be used for estimation, and the loss function is defined as follows:

$$\min_{P,Q} \frac{1}{\Omega} \sum_{(u,i)\in\Omega} (r_{ui} - p_u^T q_i) + \lambda \left\{ \sum_{u=1}^{n} J(p_u) + \sum_{i=1}^{m} J(q_i) \right\}. \tag{2}$$

The above represents the framework of the regularized latent factor model; however, this model has certain limitations. Specifically, it does not take advantage of user–item-specific network information. The explicit relationship networks of users and items can often reflect dependencies between users, yet this model does not incorporate such information. It should be noted that there are three types of relationship networks considered here: the first is the explicit social network between users; the second is the explicit social network between items; and the third is the relationship network calculated based on the known “user–item” discrete covariates (rating matrix).

II. B. BERT-LSTM Network

Social media rumor detection methods are generally divided into two categories: *post-based detection models* and *event-based detection models*.

Post-based detection models identify whether a single post is a rumor:

$$F_d(p) \rightarrow \begin{cases} \text{Rumor}, \\ \text{Non-rumor}, \end{cases} \tag{3}$$

where p represents an individual post.

Event-based detection models, on the other hand, determine whether an event—consisting of a set of posts—is a rumor:

$$F_d(E) \rightarrow \begin{cases} \text{Rumor}, \\ \text{Non-rumor}, \end{cases} \tag{4}$$

where E is an event composed of multiple posts.

The social media rumor detection model based on the BERT-LSTM network belongs to the event-level detection category. The overall framework of the BERT-LSTM network is shown in Figure 1. This network first captures long-distance semantic relationships between words in posts using BERT, and then employs an LSTM network to more comprehensively capture event-level features, ultimately enabling accurate rumor event detection.

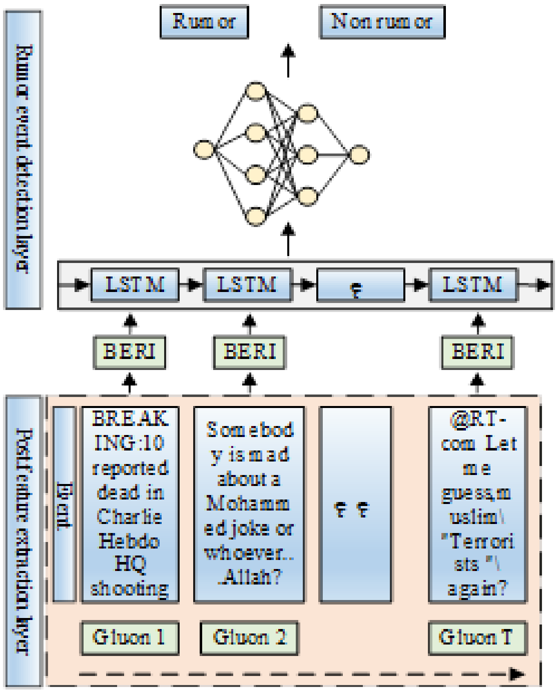

Figure 1: Framework of the rumor detection model based on BERT-LSTM.

As shown in Figure 1, the post feature extraction layer based on BERT is primarily composed of two parts: the embedding layer and the bidirectional transformer encoder.

II. C. Introducing the Implicit Relation Network into the SVD Collaborative Filtering Algorithm

In the previous section, the introduction of a relationship network structure into the SVD collaborative filtering algorithm was discussed, along with three types of networks in the smooth neighborhood recommendation algorithm. The first type is the known social relationship network between users. The second type is the similarity relationship network between items, calculated using known item label information. The third type is the similarity relationship network between users and items, calculated separately using the "user–item" rating matrix.

The first two types of relational networks can be regarded as auxiliary information in addition to the rating matrix. In practical applications, the algorithm does not perform matrix transformation on these networks; instead, it assigns weights to different relational networks when calculating the comprehensive weight.

Since no additional data mining work is involved, the network is directly used during the computation process. In this paper, the first two types of relational networks are referred to as *explicit relational networks*. However, the direct use of explicit relational networks presents certain limitations. For example, in the case of a user social relationship network, the matrix often suffers from a severe sparsity problem—usually even sparser than the "user–item" rating matrix. Furthermore, the nonzero values in the matrix are typically binary (0 or 1), indicating only the presence or absence of a relationship, without conveying the strength of that relationship.

To address these issues, this paper proposes the use of an implicit trust inference method to establish a trust propagation model. This model is then used to construct an *implicit relationship network* between users, referred to as a *trust-degree network*. This implicit relationship network is subsequently combined with the smooth neighborhood recommendation algorithm to improve overall algorithm performance. The structure of the smooth neighborhood recommendation algorithm incorporating the implicit relation network is shown in Figure 2.

The framework of the BERT-based post feature extraction layer proposed in this chapter is shown in Figure 3.

For networks with multiple nodes and edges, this paper simplifies them into a structure consisting only of user nodes, with edges representing connections between users. This is achieved through feature extraction and model transformation, as

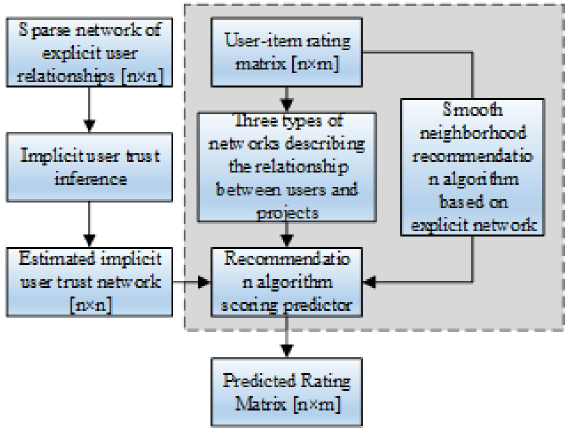

Figure 2: SVD algorithm architecture.

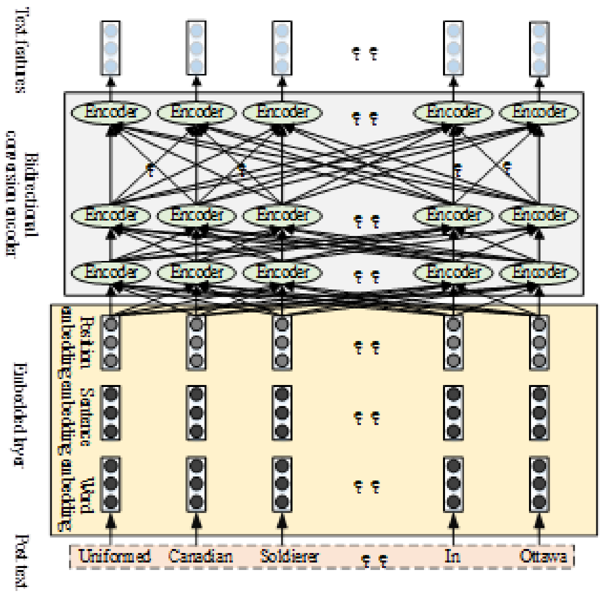

Figure 3: Post feature extraction layer based on BERT.

illustrated in Figure 4. In this representation, all available data is expressed in terms of the strength of social relationships, corresponding to the weights of edges in the network.

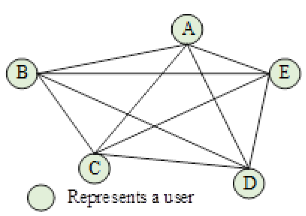

Figure 4: Structure network of social relationship strengths among users.

It is important to note that in practical applications, the matrix representing trust degrees is typically very sparse. This is because it is unrealistic to expect a single user to interact explicitly with every other user while also publishing their trust statements. As a result, the information available in the matrix is often limited.

Before calculating trust between users, it is necessary to understand how trust is transmitted. For this purpose, this paper defines four trust information flow modes, illustrated in Figure 5.

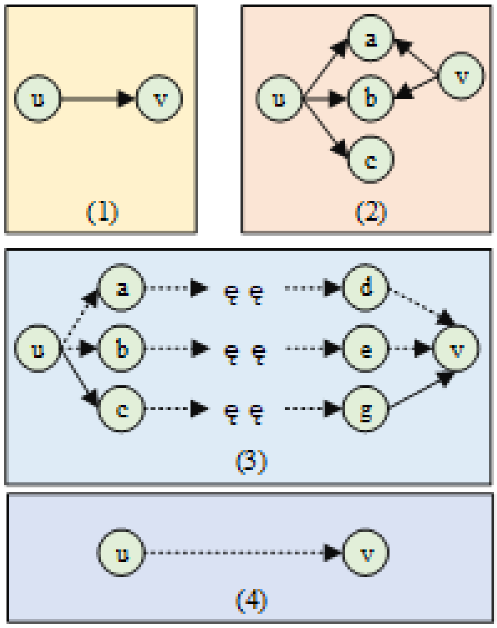

Figure 5: Four types of trust information flow patterns.

Once the trust propagation modes are understood, the trust degree between users can be calculated using the following formula:

$$\hat{t}(u,v) = \frac{|S(u) \cap S(v)|}{|S(u) \cup S(v)|}, \tag{5}$$

where $S(u)$ and $S(v)$ denote the sets of connections for users u and v, respectively.

III. Experiment

Since the survey used in this study collected data in a self-reported manner from participating users, it is necessary to test the validity of the data for potential common method bias.

The results of descriptive statistics and correlation analysis are presented in Table 1. All reported correlations reach statistically significant levels.

Table 1: Descriptive statistics and correlation analysis results ($n = 665$).

	M	SD	Fear of missing	Self-control	Social media addiction
Fear of missing	21.55	6.23	–		
Self-control	99.95	19.43	0.62***	–	
Social media addiction	77.97	20.95	0.36***	0.52***	–

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

According to the survey results, there is a strong correlation between dependence on social media, fear of missing out, and self-control. This satisfies the statistical requirements for further analysis of the self-regulation effect.

First, Model 1 was applied to test the influence of the independent variables on the dependent variable. Model 1 is a simple moderation model, controlling for the gender and age of participants in the analysis. The results are shown in Table 2.

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. All variables in the model are standardized before being entered into the regression equation.

Individual social cognition, emotions, and behaviors are frequently and extensively expressed on social media platforms. During information transmission, individuals with similar cognition, common goals, and a shared sense of belonging tend to form groups through information interaction. This is illustrated in Figure 6.

Among the user behavior characteristics, the recommendation effect based on social psychological behavior features outperforms the effect achieved by simply concatenating features. This is because the former utilizes behavioral data from users

Table 2: Adjustment model test of self-control.

Regression equation ($n = 667$)		Fitting index			Coefficient significance	
Outcome variable	Predictor	R	R^2	F	B	t
Social media addiction	Fear of missing	0.49	0.24	70.33	0.47	3.33***
	Self-control				0.47	10.04***
	Fear of missing × Self-control				0.02	2.62**
	Gender				-5.83	-4.16***
	Age				-0.94	-1.33
	Grade				1.93	2.63**

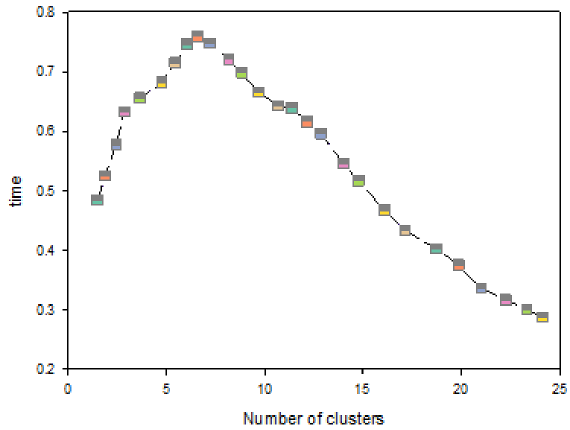

Figure 6: Selection of the optimal number of clusters k.

who repeatedly compare similar products before placing an order. Such data contains rich preference information, enabling the extraction of more representative feature vectors and improving recommendation accuracy.

As shown in Figure 7, for user comment features, the SVD model proposed in this paper demonstrates significant improvement over traditional DTM and LDA models. This is primarily because the proposed model considers the temporal dynamics of the corpus, employing a dynamic topic model for text analysis. To address the limitations of the DTM model's time-slice division, an adaptive division method is proposed, improving topic extraction accuracy. The time-decay function aligns with the evolution of user interests, ensuring that calculated user comment vectors are closer to users' current preferences, thereby enhancing the system's average recommendation accuracy.

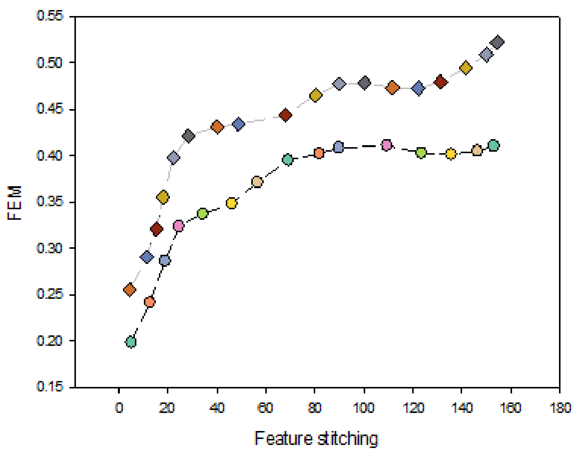

Figure 7: Comparison of user behavior feature algorithms with existing algorithms.

As shown in Table 3, the KMO value of 0.703 lies between 0.7 and 0.8, indicating that the dataset is suitable for extracting meaningful information.

Table 3: KMO check.

KMO and Bartlett's Test		
KMO value		0.703
Bartlett sphericity test	Approx. chi-square	363.624
	df	3
	p-value	0.000

Similarly, Table 4 shows a KMO value of 0.745, also within the 0.7–0.8 range, again confirming suitability for information extraction.

Table 4: Extraction information verification.

KMO and Bartlett's Test		
KMO value		0.745
Bartlett sphericity test	Approx. chi-square	1357.982
	df	15
	p-value	0.000

The User Self-Control Scale evaluates a user's self-control ability across three dimensions: social psychology, behavioral self-control, and emotional/thinking self-control. It includes six factors: online social interaction preference, emotional changes, negative consequences and persistent use, compulsive use and withdrawal, significance, and recurrence—comprising a total of 26 items, with no reverse-scored items.

Participants were informed that the questionnaire was anonymous before taking the test to reduce concerns and ensure authentic responses. All valid data were analyzed using SPSS 25.0 for descriptive statistics.

Compared with baseline models, the SVD model proposed in this paper achieves the best performance in most cases and outperforms other rumor detection methods, as shown in Table 5.

Table 5: Detection performance on the Pheme dataset.

Model	Accuracy (A)	Class	Precision (P)	Recall (R)	F1
SVM-TS	0.636	R	0.666	0.613	0.636
		N	0.631	0.635	0.637
CNN	0.653	R	0.653	0.633	0.641
		N	0.665	0.642	0.655
CRU	0.734	R	0.727	0.738	0.736
		N	0.743	0.715	0.727
CallAtRumors	0.775	R	0.777	0.773	0.775
		N	0.753	0.774	0.765
MKEMN	0.765	R	0.764	0.767	0.766
		N	0.754	0.799*	0.776*
MMEN	0.824	R	0.833	0.894	0.866
		N	0.793	0.693	0.736

Social media has made it increasingly convenient to obtain social information. However, as shown in Figure 8, this change is not evident in the Pheme dataset. This is likely because the dataset is collected from five emergent events, each containing posts related to the same event. Consequently, increasing or decreasing the number of adjacent posts has little impact on the final detection result.

Social information refers to various types of information obtained through social media platforms, including social life updates, commercial marketing messages, traditional media reports, and government service announcements. As long as there is user engagement, this information can be pushed directly to one's social media feed. The resulting word-of-mouth marketing model of social media not only leverages student user relationships but also capitalizes on the principles of individual inertial psychology.

Within the social media communication environment, the traditional concept of the "gatekeeper" is deconstructed. Although individuals' social cognition and attitudes are highly personalized, and their social characteristics within groups vary greatly, the social psychology of individuals often reflects sensitivity to group norms. Based on user relationships, this study confirms that self-control, as an individual factor, plays a regulatory role in the relationship between social media addiction and fear of missing out. This finding not only identifies the pathways through which fear of missing out influences the tendency toward social media addiction but also deepens our understanding of social media addiction, users' self-development, and their psychosocial adaptation.

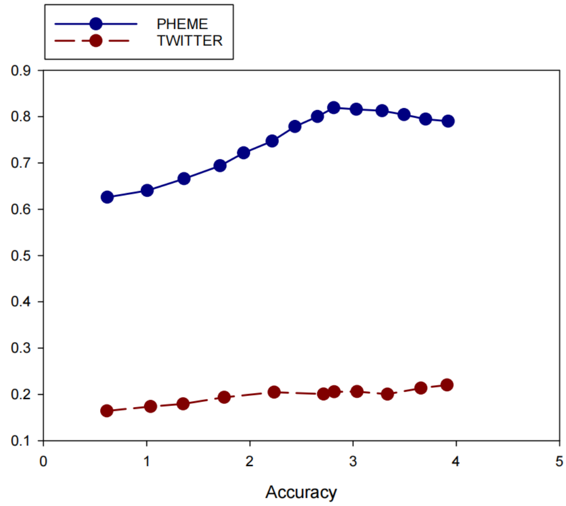

Figure 8: Accuracy results of different convolution kernel widths on Pheme and Twitter datasets.

IV. Conclusion

Student social media users are in a stage of rapid self-development and have strong communication needs. When these needs are unmet in real life, they may turn to the virtual world. Educators should identify students with high fear of missing out, anxiety, or problematic usage and intervene through parental monitoring, school counseling, and targeted psychological support. Additionally, structured educational programs should promote balanced social media use, foster self-control, and encourage healthy online habits.

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