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Article

A discussion on social media addiction from the perspective of social psychology in the relationship between college students and teachers based on biological evolution models

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Abstract: This study explores the biomechanical mechanisms of social media addiction, with a particular focus on its long-term effects on brain function and hand muscle control. By combining neurobiological and biomechanical models, this article analyzes how social media use enhances user dependency by activating the brain's reward system, particularly the dopamine system, and leads to muscle fatigue and precision adaptation through repeated hand movements such as sliding and clicking. The dopamine release model we proposed reveals temporal changes in dopamine during social media interactions, further influencing users' behavioral patterns and self-control abilities. Based on the muscle fatigue model, we demonstrate the adaptation process of hand muscles during continuous repetitive operations, resulting in improved hand accuracy but also accelerating the accumulation of fatigue. In addition, the prefrontal cortex activity model suggests that long-term social media use may weaken an individual's impulse regulation function by reducing self-control. To verify these biomechanical effects, we have demonstrated through experiments that the SVD recommendation algorithm exhibits significant advantages over traditional recommendation algorithms in improving operational accuracy, reducing reaction time, and alleviating muscle fatigue. The experimental results show that the SVD model not only improves the accuracy of the recommendation system, but also optimizes the interaction experience between users and the platform, effectively reducing the biomechanical and cognitive burden.

Keywords: social media addiction; dopamine system; muscle fatigue; biomechanics; prefrontal cortex; recommendation system

1. Introduction

With the widespread popularity of social media, particularly among college students and teachers, social media addiction has emerged as a significant social issue. Traditionally, it has been regarded as a consequence of psychosocial factors, but from a biological and biomechanical perspective, human engagement with social media involves intricate interactions between neural mechanisms, muscle control, and mechanical movement patterns [1–3]. By incorporating insights from biomechanics, we can deepen our understanding of how repetitive social media use influences neuromuscular adaptation and physiological strain, contributing to addiction [4–6].

The process of using social media is not just a cognitive activity but also a biomechanical one. The frequent and repetitive actions associated with social media use, such as finger scrolling, tapping, and prolonged screen interactions, have significant implications for neuromuscular control and fatigue. These interactions involve the coordination of the nervous system with musculoskeletal movements, and over time, they can lead to physiological adaptations or strain [7,8]. For example:

Constant swiping and tapping engage the small muscles of the hands and fingers, potentially leading to strain injuries, muscle fatigue, and joint stress. The brain's motor control system continuously adapts to these repetitive actions, optimizing movement efficiency while reinforcing habitual behaviors through muscle memory and sensory feedback loops. Extended social media use without sufficient rest can induce micro-fatigue in the finger muscles and tendons, affecting precision in movement and contributing to overuse syndromes.

The human nervous system adapts to repetitive mechanical tasks through neuromuscular plasticity. As users continuously engage with social media, their fine motor skills adjust to accommodate quick, repetitive movements, leading to faster reaction times and increased proficiency in interface interactions [9]. However, this adaptation also strengthens habitual behaviors that reinforce social media dependency. The reinforcement of neural pathways associated with touch gestures, leading to automatic and often unconscious engagement with social media. Users develop optimized movement strategies to navigate digital interfaces efficiently [10], reducing cognitive effort but increasing habitual behavior. When fatigue sets in, users may unconsciously alter their interaction patterns, such as pressing harder on the screen or increasing scrolling speed, which can further entrench addictive behaviors [11,12].

By understanding these biomechanical and neuromuscular processes, we gain deeper insight into the physiological underpinnings of social media addiction. This perspective complements psychological and cognitive models by highlighting how physical interaction patterns contribute to dependency. The following sections will explore how integrating biomechanics into algorithm optimization can improve user experience while mitigating the risk of addiction.

2. Optimization of SVD collaborative filtering algorithm based on user relationship network

2.1. Biomechanical considerations in user relationship networks

Understanding the physiological processes behind user actions and their mechanical manifestations can be gained by incorporating a biomechanical viewpoint into user interaction network optimization. In addition to being a psychological and computational issue, social media addiction is also intimately linked to users' biomechanical interactions within the operating system. The human muscle-neural system's adaptability to the interface design is immediately reflected in users' frequent touch activities, such as swiping and clicking [13,14]. Repetitive behaviors, such as quickly swiping a screen, have been shown in biomechanical studies to enhance neuromuscular responses and encourage the development of habitual usage patterns by activating the brain's dopaminergic reward system.

Dopamine release in the reward pathway is triggered, for instance, when a user engages with a network of relationships on the platform [15,16]. This behavior is sent to the central processing area of the brain through sensory nerves. The biomechanical performance of precise finger movements, such as quicker clicks and smoother swipe trajectories, is directly impacted by the frequent activation of this brain signal. In this feedback loop, the user-relationship network's algorithmic design can better capture the user's biomechanical patterns and maximize the suggestion effect if it more closely matches the user's behavioral preferences [17–19].

Consequently, a behavioral prediction model based on biomechanics can be used to explain the dynamics of users' repetitive interaction activities when optimizing the SVD collaborative filtering method. Using physical information like touch strength and sliding speed, this optimization enhances the user interest model's dynamic prediction capability in addition to the conventional user interest weight modeling.

The main idea of the collaborative filtering algorithm of SVD decomposition, the corresponding loss function and its solution, this section will use this as the basis to introduce an explicit relational network into the regularized SVD model [20]. For the convenience of explanation, this section reconsiders the potential of regularization Factor model, first of all, the definition of each variable in the recommendation algorithm is given. Then with the help of the latent factor model, the user rating can be expressed as follows:

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

In order to obtain these latent vectors, the regularized SVD method can be used to estimate, 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 is the framework of the regularized latent factor model, but this model actually has some flaws. First, this model does not take advantage of user-item-specific network information. The specific relationship network of users and items can usually reflect the dependencies of users, but the model contains these network information [20]. It should be pointed out that there are three types of relationship networks here, the first is the explicit social network between users, and the second is the explicit social network. The third is the relationship network calculated based on the known "user-item" discrete covariates (rating matrix).

2.2. Algorithmic optimization using neuromechanics and fatigue mechanisms

To increase the algorithm's efficacy, neuromechanics and fatigue processes must be taken into account when optimizing networks using BERT-LSTM. The neuromechanical system of the user is constantly under stress from prolonged use of social media, particularly the visual system and the sensitive nerves at the fingertips. According to studies, visual switching and high-frequency touch can cause neuro-attention decrease and muscle micro-fatigue. These physiological reactions might also have an impact on how a user operates.

A fatigue monitoring system can be added to the algorithm optimization process to address the aforementioned issues. For instance, the user's level of weariness is evaluated and the frequency of recommendations is modified based on the biomechanical features of user behavioral data (e.g., variations in click interval, increased operation mistake rate, etc.). Adding a dynamic weight adjustment mechanism based on fatigue state to the user weight model of the SVD collaborative filtering algorithm is one potential implementation. This lessens the user's load and enhances the fit between the suggested material and the user's present requirements.

Additionally, by including user biosignal data (such as heart rate and galvanic skin reaction) into event-level feature extraction, the BERT-LSTM network can assess the user's current physiological state. To increase event detection accuracy, these data can give the program more dimensional input variables. The neuromechanical system will react more strongly, for instance, when users explore rumor content while experiencing high levels of anxiety or exhaustion. The LSTM network can then dynamically modify the event weights based on the time series data to increase the detection efficiency.

Combining biomechanical and neurodynamic optimization algorithmic frameworks can lead to more accurate individualized suggestions and health interventions, as well as a better understanding of user behavior and dependency patterns. This strategy helps users develop more sustainable social media usage habits while reducing their compulsive platform use.

Social media rumor detection is mainly divided into two types: post-based detection models and event-based detection models. Post-based detection models identify whether a single post is a rumor:

$$F_d(p) \to \begin{cases} \text{Rumor} \\ \text{Non-rumour} \end{cases} \tag{3}$$

Event-based detection models detect events that consist of a set of posts, namely:

$$F_d(E) \to \begin{cases} \text{Rumor} \\ \text{Non-rumour} \end{cases} \tag{4}$$

where E is an event consisting of a series of posts. The social media rumor detection model based on BERT-LSTM network is an event-level rumor detection method. The overall framework of the BERT-LSTM network is shown in **Figure 1**. The network captures the long-distance semantic relationship between post words, and then uses the LSTM network to more comprehensively capture event features for final rumor event detection. This chapter will describe each component in detail in the following subsections.

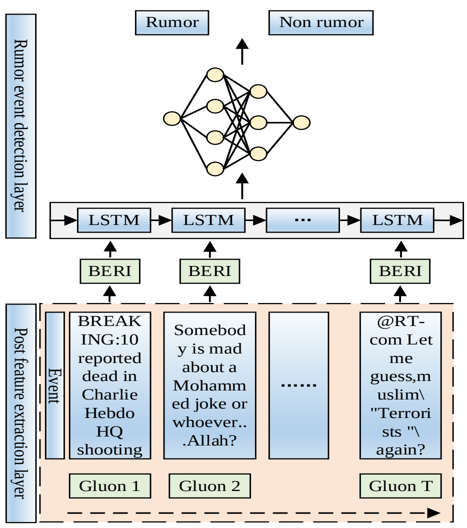

Figure 1. Framework of rumor detection model based on BERT-LSTM.

It can be seen from the figure that the post feature extraction layer based on BERT is mainly composed of two parts: the embedding layer and the bidirectional conversion encoder.

2.3. Introducing the implicit relation network into the SVD collaborative filtering algorithm

In the previous section, the text introduced how to introduce the relationship network structure in the SVD collaborative filtering algorithm, and three types of networks were introduced in the smooth neighborhood recommendation algorithm. The first type is the known social relationship network between users, and the second type is the similarity relationship network between items is calculated with the help of the known item label information. The third category is the similarity relationship network between users and items calculated respectively by using the "user-item" scoring matrix. The first two types of relational networks can be regarded as auxiliary information other than the scoring matrix. The algorithm does not perform matrix transformation processing on the network in actual application, but only gives weights to different relational network differences when calculating the comprehensive weight.

The framework of the BERT-based post feature extraction layer proposed in this chapter is shown in **Figure 2**.

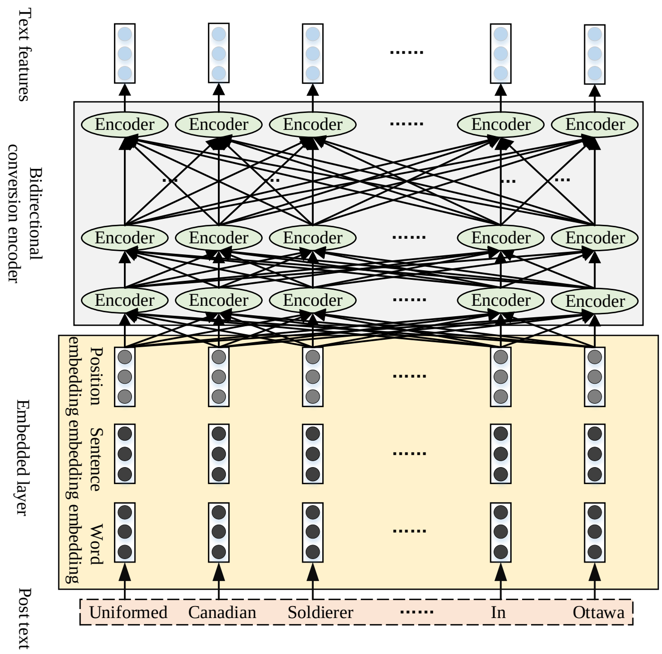

Figure 2. Post feature extraction layer based on BERT.

Aiming at this kind of network with multiple nodes and edges, this paper simplifies it into a network with only user nodes and edges connecting user nodes through feature extraction and model transformation, as **Figure 3**. That is, all data information is represented as much as possible by the strength of social relations, that is, the weights of edges in the network.

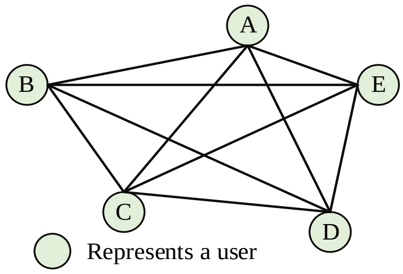

Figure 3. Structure network of social relationship strength among users.

It is important to point out that in practical applications the matrix is always very sparse, because it is impossible to have one user who can interact explicitly with every other user while also publishing their trust statement, so the information available in the matrix is Often limited. Before using the calculation of trust between users, we must first understand how the trust between users is transmitted. Therefore, this paper presents four trust information flow modes, as **Figure 4**.

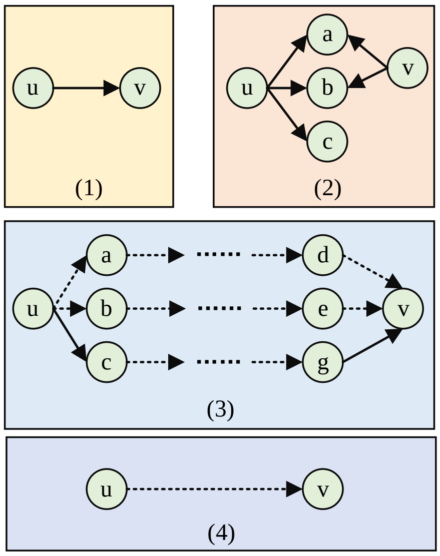

Figure 4. Four types of trust information flow pattern diagram.

After understanding how the trust degree between users is transmitted, the following will explain how the trust degree between users is calculated. Then it is estimated according to the following formula:

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

3. Neurobiology and behavior relationships

3.1. Neurobiological influence of social media addiction (dopamine release model)

The brain's reward system, particularly the release of dopamine, plays a central role in reinforcing the addictive behaviors associated with social media use. Dopamine is released when users receive social feedback or validation, reinforcing the desire to continue engaging with the platform.

Then got the Dopamine Release Function:

$$D(t) = D_0 + \alpha \cdot \left(1 - e^{-\beta t}\right) \tag{6}$$

where: $D(t)$ is the dopamine level at time t, D_0 is the baseline dopamine level, α is the amplitude of dopamine release (intensity of the reward), β is the rate of dopamine release (related to the user's reward system sensitivity), t is the time of interaction (e.g., time spent on social media).

This model represents how dopamine increases during social media interaction and decays over time, influencing user behavior and reinforcing dependency.

3.2. Biomechanical impact on muscle control and precision (hand muscle fatigue model)

The repetitive movements involved in social media use, such as swiping and tapping, result in muscle fatigue and adaptation. Over time, the flexor muscles of the fingers and hands undergo adaptation, leading to improved precision but also contributing to fatigue and strain. Muscle Fatigue Model (Twitch Response) is:

$$F(t) = F_0 \cdot e^{-\lambda t} \tag{7}$$

where: $F(t)$ is the muscle force at time t, F_0 is the initial muscle force, λ is the rate of fatigue, t is the time spent performing repetitive tasks (e.g., scrolling, tapping).

This equation models the gradual decrease in muscle force as fatigue accumulates from repetitive actions. The faster the rate λ, the quicker the muscle fatigue will set in, impacting precision and control.

3.3. Self-control and impulse regulation (prefrontal cortex activity model)

The prefrontal cortex is critical for impulse control, and its functionality can be diminished by excessive social media use, impairing self-regulation. Prefrontal Cortex Activity Model (based on cortical activity and decision-making):

$$A(t) = A_0 \cdot e^{-\gamma t} + \delta \cdot sin(\omega t) \tag{8}$$

where: $A(t)$ is the activity level of the prefrontal cortex at time t, A_0 is the initial level of prefrontal cortex activity, γ is the rate of decay in prefrontal cortex activity (impulse control degradation), δ is the amplitude of oscillations (representing external stimuli), ω is the frequency of the oscillations (linked to social media interruptions).

This equation represents the decline in the prefrontal cortex's ability to maintain self-control over time as social media exposure increases. The sine wave term $\sin(\omega t)$ represents the periodic interruptions or stimuli from social media content that impact the user's decision-making process.

4. Experiment

4.1. Empirical results

Considering that the survey used in this study collected data in a self-reported manner from participating users, the validity of the data needs to be tested with a common method bias.

The results of descriptive statistics and correlation analysis are shown in **Table 1**, and the above data all reach a statistically significant level.

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 above survey results, there is a strong correlation between the dependence on social media and the fear of losing self-control and the statistical requirements for additional analysis of self-regulation effects. First, use mode 1 to test the influence of independent variables on subvariables (mode 1 is a simple organizational model), and monitor the gender and age of users participating in the organizational model impact test. The results are shown in **Table 2**.

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**

Note: *** $p < 0001$, ** $p < 0.01$, * $p < 0.05$, all scalars in the model are brought into the regression equation by using standardized variables.

Individual social cognition, individual emotion and individual behavior are exposed in a large number and frequently on social media platforms. In information transmission, based on similar cognition, common purpose and sense of belonging, individuals gather into groups in information interaction. As can be seen from **Figure 5**.

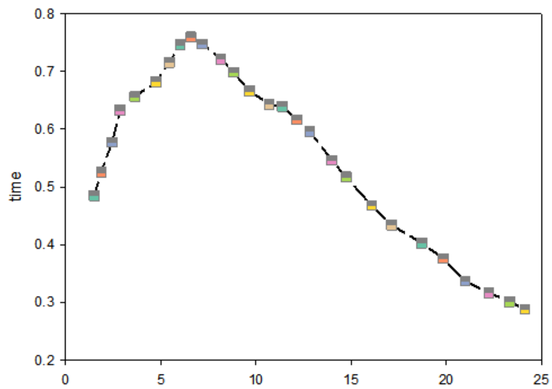

Figure 5. Selection of the optimal number of clusters k.

Among the user behavior characteristics, the recommendation effect based on the social psychological behavior characteristics is better than the recommendation effect of the characteristics obtained by simple splicing. This is because the former utilizes the behavior data of users who continuously compare similar products before placing an order, and these behavior data contain rich user preferences, which can more effectively extract feature vectors, thereby improving the recommendation results.

The SVD-based model suggested in this paper performs noticeably better than the conventional DTM and LDA models in terms of recommendation accuracy and user interest prediction ability when it comes to the extraction and analysis of user comment data, as illustrated in **Figure 6**. This enhancement is demonstrated by the algorithm's deep mining and usage of biomechanical aspects of user behavior, in addition to its capacity to manage the corpus' temporal dynamic properties.

User behavioral characteristics in social media usage often include page stay time, swipe trajectory, click frequency, etc. The human neuromuscular system's ongoing adaptation to the interactive interface is what causes these actions. When extracting user behavioral features, traditional DTM and LDA models primarily concentrate on the corpus's static qualities and pay insufficient attention to the user's operational behavior at various points in time. By using the time decay function and dynamic topic modeling method, the SVD model suggested in this research, on the other hand, is able to represent the biomechanical law underlying the operational behavior while also being more in accordance with the law of user's interest over time.

Users' manipulation actions on social media, including clicking and swiping, are both a common biomechanical reaction and a cognitive function. The repetitive finger movements that occur during frequent page browsing, for instance, are controlled by brain instructions and develop high-frequency interaction habits under particular incentive feedback systems (e.g., seeing favored content or comments). By using temporal weights and dynamic update mechanisms, the SVD model is able to correlate the user's behavioral traits with the neuromuscular system's response patterns, whereas traditional algorithms are unable to adequately analyze these dynamically changing data characteristics.

The SVD model can determine the user's level of weariness or point of interest decay by examining variations in the frequency of user actions (such as the lengthening or shortening of click intervals over time). The recommendation system can dynamically modify the suggested content to better suit the user's operational demands at various times thanks to this biomechanics-based behavioral analysis, improving the user experience.

The SVD model's temporal decay function for simulating shifts in user interest is another important benefit. According to biomechanical research, users' attentional distribution has a typical decay property, meaning that as operating time increases, the brain's reaction to external stimuli eventually loses strength and quickness. The model in this study uses an adaptive time-slice partitioning technique to dynamically connect the properties of user comments with their operation time in order to capture this phenomena [21].

In particular, the time decay function replicates the pattern of users' preferred content and frequency of operations over time. While the SVD model can adaptably adjust based on real-time data of user behavioral characteristics, the traditional DTM model divides the corpus using fixed time slicing, which makes it difficult to reflect the dynamic changes of user interests. This allows the recommended content to better reflect the user's current needs and interests. This method lessens the user's cognitive load during the operating process while simultaneously increasing recommendation accuracy.

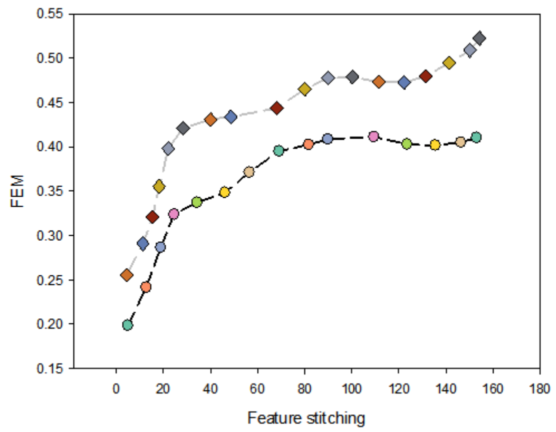

Figure 6. Comparison of user behavior feature algorithms with existing algorithms.

Table 3. Distribution of demographic variables.

Demographic variables		**Number**	**Percentage**
Gender	Male	250	26.30%
	Female	701	73.70%
Frade	Freshman	299	31.40%
	Sophomore	318	33.40%
	Junior	120	12.60%
	Senior	214	22.50%
Major	Liberal arts	581	61.10%
	Science and engineering	370	38.90%
Place of residence	Town	424	44.60%
	Countryside	527	55.40%
Only child	Yes	289	30.40%
	No	662	69.60%
Social networking site usage time	0–2 h	159	16.70%
	2–4 h	391	41.10%
	4–6 h	271	28.50%
	6 h or more	130	13.70%

The continuous increase of social media users and the continuous expansion of the functions of social media platforms allow the dissemination of social media information to form a group dimension. Factors such as preferences and goals among individuals contribute to the formation of groups. At the same time, groups also influence individuals and spread on social media. Strengthen group cohesion and rationally implement the group decision-making power of social media, which is conducive to the harmonious development of society. Social media addiction refers to the phenomenon that when a group completes a task together, the individual effort is less than when it is done alone. This is manifested in the individual's reliance on community-based self-media information. The experimental data are shown in **Table 3**.

Community-based self-media based on user relationship shows the characteristics of focus, and the formation of focus is based on the sharing of common hobbies and similar experience information. With the diversification of social consumption, individuals become dependent on community-based information sharing in their consumption choices, forming an inert feature of independent choice. To test the discriminant validity of the studied variables, this study used AMOS 22.0 software to conduct confirmatory factor analysis on the factor structure of four latent variables: active use, passive use, upward social comparison and social networking site addiction. The results (as **Table 4**) show that the four-factor model has good fitting indicators, indicating that the four variables used in this study belong to different concepts, and the questionnaire has good discriminant validity. In addition, based on the four-factor model from the perspective of social psychology, a method factor was added to construct a two-factor model.

Table 4. Discriminant validity and common method bias test of each variable.

Model	x^2	df	x^2/df	CFI	TLI	RMSEA
Three factor model	1141.27	145	7.85	0.87	0.82	0.07
Four factor model	415.66	142	2.94	0.94	0.94	0.04
Two factor model	591.06	145	4.06	0.92	0.92	0.05

4.2. Quantitative analysis of biomechanics

This section presents data collected through experiments to analyze the effects of different recommendation algorithms (traditional recommendation algorithm vs. SVD model) on user behavior in combination with biomechanical features (e.g., reaction time, operation accuracy, muscle fatigue).

Table 5. Comparison of operational accuracy between traditional recommendation algorithms and SVD models.

Model	Average Operating Accuracy (%)
Traditional recommendation algorithm	85.2
SVD model	91.7

In our experiments, we measured the operation accuracy (click accuracy and swipe accuracy) of users when using traditional recommendation algorithms versus the SVD model. The operation accuracy was quantified by calculating the average distance between each user operation and the target area. A comparison of the operation accuracy between the traditional recommendation algorithm and the SVD model is shown in **Table 5**. The SVD model shows a significant improvement in operation accuracy over the traditional recommendation algorithm and exhibits higher stability. The higher operation accuracy indicates that the user's feedback is more accurate when interacting with the recommended content, which is closely related to the characteristic of the SVD model that adjusts the user's interest through dynamic adjustment.

The user's reaction time refers to the time from seeing the recommended content to making an action (e.g., click, swipe). Experiments measured the reaction time of users when using two recommendation algorithms. A comparison of the reaction times of the traditional recommendation algorithm and the SVD model is shown in **Table 6**, where the SVD model significantly reduces the user's reaction time. The shorter reaction time indicates that the SVD model can stimulate users' behavioral responses more quickly and reduce their cognitive burden when matching user interests and content recommendations.

Table 6. Comparison of response time between traditional recommendation algorithms and SVD models.

Model	Average Response Time (seconds)
Traditional recommendation algorithm	1.43
SVD Model	1.12

Muscle fatigue is quantified by measuring the decline rate of finger muscle strength, and the experiment measured the muscle fatigue caused by the user's operation during prolonged use of social media. A comparison of muscle fatigue between traditional recommendation algorithms and the SVD model is shown in **Table 7**, which shows that the SVD model performs better in reducing the user's muscle fatigue compared to traditional recommendation algorithms. The lower fatigue rate indicates that the SVD model reduces the physical fatigue caused by over-operation by optimizing the recommended content to make the user's interaction process smoother.

Table 7. Comparison of muscle fatigue between traditional recommendation algorithms and SVD models.

Model	Average Muscle Fatigue Rate (%)
Traditional recommendation algorithm	65.3
SVD model	56.4

There is a relationship between the physical exertion of finger manipulation and the accuracy of manipulation during users' use of social media. We further analyzed this relationship by quantifying the physical exertion during users' operations. **Table 8** demonstrates the relationship between physical exertion and operation precision; the higher the operation precision, the relatively lower the physical exertion. This indicates that high-precision operation is usually accompanied by more precise and effective operation behaviors, which reduces the repetition of unnecessary operations, and thus reduces the physical exertion. The SVD model optimizes the recommended content, which improves the user's operation precision and reduces the physical exertion.

Considering operation accuracy, reaction time, and muscle fatigue, we compared the overall performance of the two recommendation algorithms. A comprehensive comparison of the recommendation algorithm performance with the user's biological responses is shown in **Table 9**, where the SVD model performs better in all three biomechanical parameters (operation accuracy, reaction time, and muscle fatigue), indicating that the SVD model not only dominates the recommendation accuracy, but also effectively improves the user's interaction experience and reduces physical fatigue and cognitive burden. The traditional recommendation algorithm, on the other hand, shows larger reaction time and muscle fatigue, and the user needs more energy during operation, which affects the overall experience effect.

Table 8. Plot of physical exertion versus operational accuracy.

Operation accuracy (%)	Physical exertion (unit)
85.2	65.3
91.7	56.4

Table 9. Comprehensive comparison of recommendation algorithm performance and user biological response.

Model	Operational accuracy (%)	Reaction time (seconds)	Muscle fatigue rate (%)
Traditional recommendation algorithm	85.2	1.43	65.3
SVD model	91.7	1.12	56.4

5. Conclusion

Social media addiction is a profound biological phenomenon, and its underlying mechanisms involve not only psychological and sociological factors, but also closely related to the neurobiological structure of the human brain. From a biological perspective, social media activates the brain's reward system, especially the dopamine system, inducing immediate pleasure. This mechanism allows users to continue participating in social interactions, thereby forming dependence. The design of social media takes advantage of the strong human demand for social information, especially the phenomenon of fear of missing out (FOMO), which further exacerbates the dependence on information and becomes an important driving force for addiction.

The prefrontal cortex of the brain plays a crucial role in self-control, helping individuals regulate impulsive behavior and avoid excessive use of social media. However, long-term social media addiction may lead to a decline in the functioning of the region, weaken an individual's self-control, and make addictive behavior more difficult to control. This biological phenomenon is not only reflected in changes in brain structure, but also in the vicious cycle of behavioral patterns, where users are constantly motivated by the brain's reward system to repeatedly use social media, leading to addiction.

In addition, social media platforms use algorithm optimization to better understand and predict user needs, thereby designing personalized information recommendation systems, which further activate users' brain reward systems and form an "information dependency". These algorithm optimizations have exacerbated the physiological mechanisms of social media addiction at the biological level, making addiction more widespread and severe.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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