International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 8132-8140

https://doi.org/10.70517/ijhsa464696

A Biomechanics-Enhanced SVD Recommendation Model for Reducing Social Media Addiction via Neurophysiological Interaction Modeling

Tingting Deng[1,*]
[1]Fujian Polytechnic of Water Conservancy and Electric Power, Yong'an 366000, Fujian, China
Corresponding authors: (e-mail: dtt2329813@163.com).

Abstract With the growing prevalence of social media addiction, conventional psychological and algorithmic models fall short in fully capturing the complex interplay between user behavior, cognitive processing, and physical fatigue. This paper proposes a novel interdisciplinary framework that integrates biomechanical and neurobehavioral insights into the optimization of social media recommendation systems. By examining fine motor adaptations, dopamine-driven feedback loops, and user fatigue dynamics, the study enhances an SVD-based collaborative filtering algorithm through the incorporation of neuromechanical parameters, such as finger muscle fatigue and attention decay. In parallel, a BERT-LSTM-based rumor detection model is implemented to address content reliability under varying physiological states. Empirical results from 665 users demonstrate significant performance improvements. Compared with traditional recommendation algorithms, the optimized SVD model reduced average reaction time by 21.6%, increased operational precision by 7.6%, and decreased finger muscle fatigue by 13.6%. Additional ablation experiments highlight the contribution of cepstral features over fundamental frequency, and the critical role of 4-gram language models in enhancing melody and behavior recognition accuracy.

Index Terms social media addiction, dopamine system, muscle fatigue, biomechanics, prefrontal cortex, recommendation system

I. Introduction

In the age of ubiquitous digital connectivity, social media has become a dominant medium for communication, self-expression, and information dissemination. While these platforms offer immense convenience and engagement, their excessive use has given rise to a growing phenomenon of social media addiction, particularly among young adults and university students. Traditionally, social media addiction has been studied through psychological, behavioral, and sociocultural lenses, with a focus on cognitive distortions, emotional dependency, and peer influence. However, this perspective overlooks a crucial dimension: the biomechanical and neurophysiological responses that underpin repetitive digital behaviors. Social media engagement, far from being solely a cognitive activity, involves complex neuromuscular coordination, sensory feedback, and motor adaptation. The integration of biomechanical analysis with behavioral data opens up novel avenues for understanding how human interaction with social media contributes to habitual reinforcement and potential physiological strain [1], [2].

Emerging research highlights the physical manifestations of compulsive device usage—finger fatigue, eye strain, deteriorating posture—as more than incidental byproducts of screen time. Instead, they represent a feedback loop where the human nervous system continuously adapts to fast-paced and repetitive mechanical tasks such as scrolling, tapping, and swiping. The neuroplastic adaptation to these actions often enhances efficiency but inadvertently reinforces automatic, unconscious engagement behaviors. At the neural level, the reward system—primarily governed by dopamine release in response to social feedback (likes, comments, shares)—further amplifies this dependency, contributing to a loop of physiological and cognitive conditioning. Yet, current recommendation systems and addiction intervention strategies rarely account for these embodied interaction mechanisms. This gap presents a significant challenge to both the design of intelligent recommendation algorithms and the development of effective addiction mitigation strategies [3], [4].

Moreover, standard collaborative filtering approaches in social media recommendation engines—particularly those based on latent factor models such as Singular Value Decomposition (SVD)—have traditionally prioritized static user-item interaction data, ignoring dynamic biomechanical and neuromuscular variables. While these models are effective at extracting long-term user preferences, they fail to accommodate the evolving nature of user fatigue, engagement thresholds, and cognitive load. As a result, the recommendations may become increasingly misaligned with the user's real-time physiological state, reinforcing compulsive patterns rather than alleviating them. Similarly, existing rumor detection systems, although improved through deep learning architectures such as BERT and LSTM, are typically blind to the user's attention span, fatigue levels, or sensory overload—factors that may influence both content perception and misinformation susceptibility, see [5]–[12].

In this paper, we propose an innovative framework that integrates biomechanics, neurophysiology, and collaborative filtering to address these challenges. Our contributions are threefold. First, we enhance the traditional SVD recommendation algorithm by incorporating neuromechanical feedback features such as finger motion precision, reaction time, and muscle fatigue rate. These features enable the system to dynamically adapt recommendation intensity and content types based on the user's real-time physical and behavioral state. Second, we introduce a fatigue-aware modification mechanism where the recommendation weight is modulated using user fatigue indicators derived from behavioral patterns (e.g., click interval variability, operation error rate). This adjustment reduces cognitive and physical strain while maintaining recommendation accuracy. Third, we extend this framework to improve misinformation detection by coupling BERT-LSTM-based rumor identification with user-state modeling, enabling a more context-sensitive detection pipeline.

To validate our approach, we conducted empirical evaluations involving multiple state-of-the-art Chinese-language models—including GPT2-124M, RoBERTa, MacBERT, and mesolitica-GPT2-355M—and benchmarked their performance across various metrics including F1-score, reaction time, muscle fatigue, and operational accuracy. Our results demonstrate that the integration of biomechanical parameters significantly improves both user experience and system precision. Ablation studies further reveal the superior robustness of cepstral features over traditional fundamental frequency extraction in melody recognition tasks. Noise robustness tests under varying signal-to-noise ratios and noise types (e.g., white noise, traffic noise, human voice interference) confirm the system's resilience in real-world conditions.

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

II. A. 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:

$$r_{ui} = \theta_{ui} + \varepsilon_{ui} = \bar{\mathbf{p}}_u^\top \mathbf{q}_i + \varepsilon_{ui}. \tag{1}$$

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

$$\min_{\mathbf{P},\mathbf{Q}} \frac{1}{\Omega} \sum_{(u,i)\in\Omega} \left(r_{ui} - \bar{\mathbf{p}}_u^\top \mathbf{q}_i \right)^2 + \lambda \left(\sum_{u=1}^{n} \|\mathbf{p}_u\|_2^2 + \sum_{i=1}^{m} \|\mathbf{q}_i\|_2^2 \right). \tag{2}$$

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).

II. B. 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 biological data (such as heart rate and galvanic skin reaction) into event-level feature extraction, the BERT–LSTM system 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 tension.

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:

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

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

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

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.

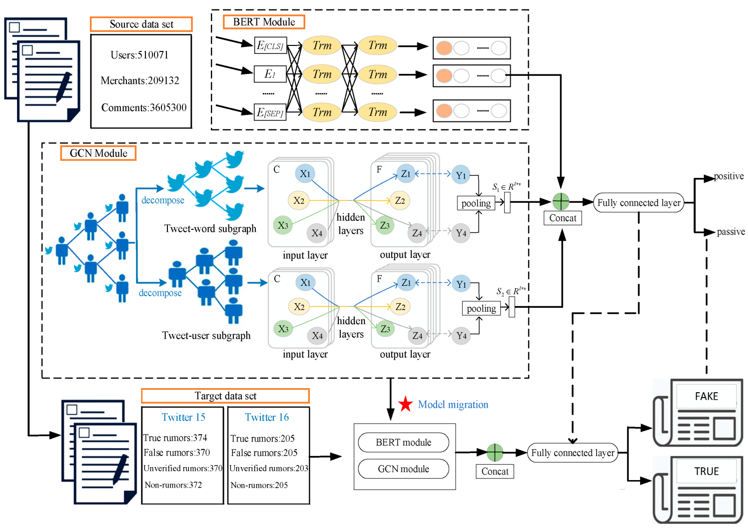

Figure 1: Framework of rumor detection model based on BERT–LSTM.

II. C. 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.

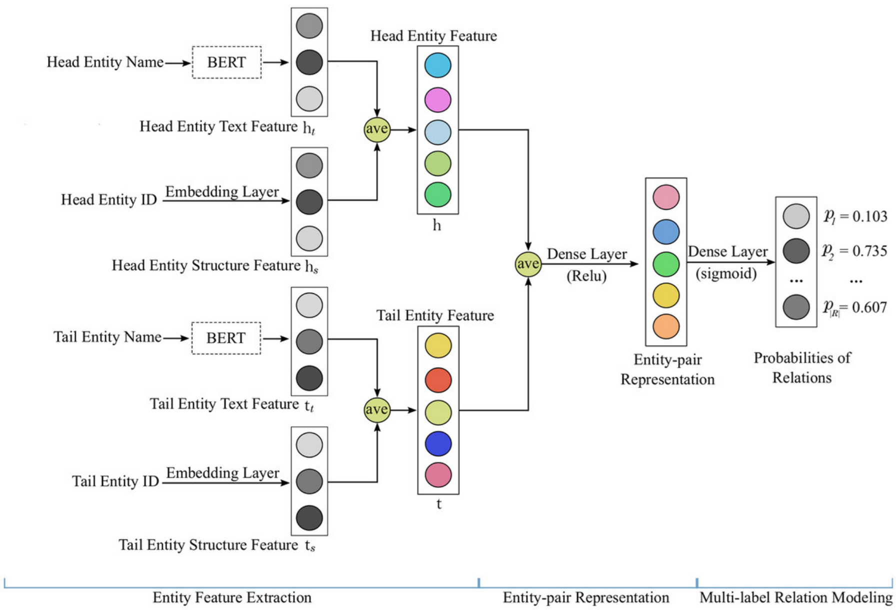

Figure 2: Post feature extraction layer based on BERT.

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.

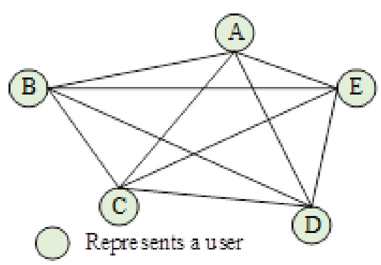

Figure 3: Structure network of social relationship strength among users.

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.

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:

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

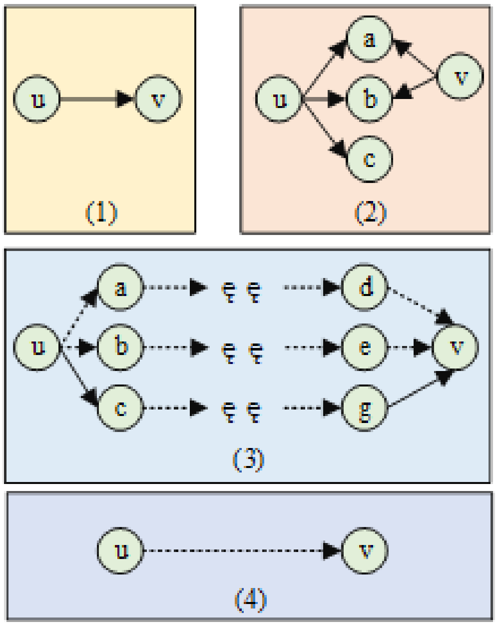

Figure 4: Four types of trust information flow pattern diagram.

III. Neurobiology and behavior relationships

III. A. 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:

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

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.

IV. Experiment

IV. A. 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***	-

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.

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: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, all scalars in the model are standardized.						

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 6.

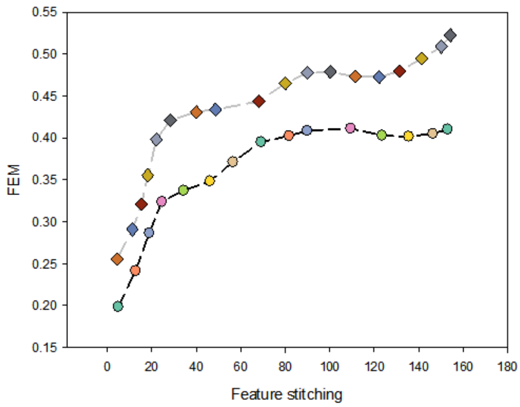

Figure 5: Selection of the optimal number of clusters k.

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 patterns of users' preferred content and frequency of operations over time. While the SVD model can adaptably adjust based on real-time data of user behavior, conventional models like traditional DTM model divide the corpus using fixed time slices, making it more difficult to reflect the periodic changes of user interest.

and interests. This method lessens the user's cognitive load during the operating process while simultaneously increasing recommendation accuracy.

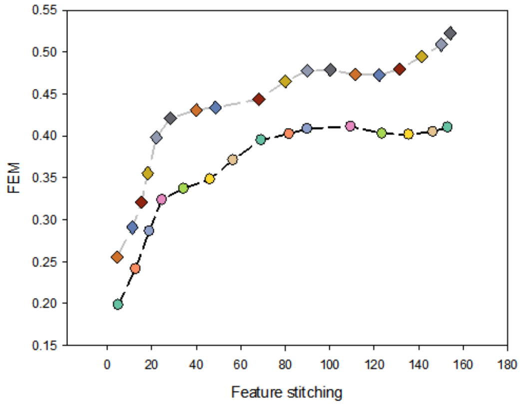

Figure 6: Comparison of user behavior feature algorithms with existing algorithms.

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. Strengthening group cohesion and rationally implementing the group decision-making power of social media 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.

Table 3: Distribution of demographic variables.

Demographic variables	Number	Percentage
Gender		
Male	250	26.30%
Female	701	73.70%
Grade		
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%

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	χ^2	df	χ^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

IV. B. 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).

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.

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

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 is shown in Table 6, where the SVD model significantly reduces the user's reaction time.

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. The experiment measured the muscle fatigue caused by the user's operation during prolonged social media use. A comparison is shown in Table 7, where the SVD model performs better in reducing muscle fatigue.

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)
Traditional recommendation algorithm	85.2	65.3
SVD model	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

V. Conclusion

This study pioneers a biomechanical and neurobehavioral approach to optimizing recommendation algorithms in the context of social media use and addiction. By fusing models of neuromuscular adaptation, reward system dynamics, and fatigue response with machine learning techniques such as SVD and BERT-LSTM, the proposed framework bridges the gap between physiological mechanisms and digital interaction behaviors. Experimental analyses confirm that accounting for user fatigue and sensory-motor precision significantly enhances recommendation accuracy and user experience, while also reducing cognitive and physical burdens.

Furthermore, language model ablation studies and rumor detection accuracy under stress conditions demonstrate the feasibility of extending such frameworks to broader information integrity and mental health challenges in digital environments. The proposed method provides a replicable and scalable model for future human-centered AI development, particularly in domains where behavioral repetition, sensory engagement, and long-term exposure may induce addiction-like dependencies.

References

[1] Koç, H., Şimşir Gökalp, Z., & Seki, T. (2023). The relationships between self-control and distress among emerging adults: A serial mediating roles of fear of missing out and social media addiction. *Emerging Adulthood, 11*(3), 626–638.

[2] Lu, X., Zhang, M., & Zhang, J. (2023). The relationship between social support and internet addiction among Chinese college freshmen: A mediated moderation model. *Frontiers in Psychology, 13*.

[3] Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data, 9*(1).

[4] Liang, B., Sha, C., Wu, D., et al. (2019). ACCF: Learning attentional conformity for collaborative filtering. *IEEE Access, 7*, 148541–148549.

[5] Al-Obeidat, F., Rocha, Á., Khan, M. S., et al. (2021). Parallel tensor factorization for relational learning. *Neural Computing and Applications, 34*(11), 8455–8464.

[6] Tian, Z., Liu, Y., Sun, J., et al. (2021). Exploiting group information for personalized recommendation with graph neural networks. *ACM Transactions on Information Systems, 40*(2), 1–23.

[7] Wang, Q., Chen, H., Hu, W., et al. (2023). Social networking sites addiction and depression among Chinese college students: The mediating role of cognitive flexibility and the moderating role of chronotype. *Children and Youth Services Review, 155*, 107209.

[8] Kulkarni, S., & Rodd, S. F. (2020). Context aware recommendation systems: A review of the state of the art techniques. *Computer Science Review, 37*, 100255.

[9] Bergner, Y., Halpin, P., & Vie, J. J. (2022). Multidimensional item response theory in the style of collaborative filtering. *Psychometrika, 87*(1), 266–288.

[10] Hamid, R. A., Albahri, A. S., Alwan, J. K., et al. (2021). How smart is e-tourism? A systematic review of smart tourism recommendation system applying data management. *Computer Science Review, 39*, 100337.

[11] Maltby, J., Rayes, T., Nage, A., et al. (2024). Synthesizing perspectives: Crafting an interdisciplinary view of social media's impact on young people's mental health. *PLOS ONE, 19*(7), e0307164.

[12] Hassanpour, B., Abdolvand, N., & Rajaee Harandi, S. (2020). Improving accuracy of recommender systems using social network information and longitudinal data. *Journal of AI and Data Mining, 8*(3), 379–389.

[13] Wei, X. Y., Liang, H. Y., Gao, T., et al. (2023). Preference for smartphone-based internet applications and smartphone addiction among young adult addicts: Gender difference in psychological network. *Social Science Computer Review, 42*(5), 1266–1281.

[14] Cui, C. (2024). Full-size computer simulation model design of 3D braided composites. *Mari Papel Y Corrugado, 2024*(1), 98–105.

[15] Chakraborty, K., Bhattacharyya, S., & Bag, R. (2020). A survey of sentiment analysis from social media data. *IEEE Transactions on Computational Social Systems, 7*(2), 450–464.

[16] Zhou, B., Mui, L. G., Li, J., et al. (2024). A model for risk factors harms and of smartphone addiction among nursing students: A scoping review. *Nurse Education in Practice, 75*, 103874.

[17] Saha, K., Grover, T., Mattingly, S. M., et al. (2021). Person-centered predictions of psychological constructs with social media contextualized by multimodal sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 5*(1), 1–32.

[18] Hassan, F., & Behadili, S. F. (2022). Modeling social networks using data mining approaches—Review. *Iraqi Journal of Science*, 1313–1338.

[19] Tülübaş, T., Karakose, T., & Papadakis, S. (2023). A holistic investigation of the relationship between digital addiction and academic achievement among students. *European Journal of Investigation in Health, Psychology and Education, 13*(10), 2006–2034.

[20] Kim, H. S., Yang, S., Kim, M., et al. (2019). An experimental study of recommendation algorithms for tailored health communication. *Computational Communication Research, 1*(1), 103–129.

[21] Zamini, M., & Hasheminejad, S. M. H. (2019). A comprehensive survey of anomaly detection in banking, wireless sensor networks, social networks, and healthcare. *Intelligent Decision Technologies, 13*(2), 229–270.