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# *Media, Algorithms, and Attention: An Empirical Analysis of Influencing Factors and Gender Differences*

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***Abstract:*** This study explores the factors that affect human attention, especially for an in-depth study of short video platforms and AI recommendation algorithms. In modern times, due to the development of network technology, the popularity of fragmented digital content and the immersion brought by recommendation algorithms have led to the continuous decline of attention span and cognitive depth. In this study, multiple regression models were constructed by integrating behavioral, psychological, and environmental variables to explore the main factors affecting attention. Data from 300 participants in the questionnaire showed that user interaction behavior and AI algorithm perception significantly affected attention levels, while the variables of living habits and self-control showed different effects. Further analysis based on gender shows the differences of certain influencing factors between male and female users. These results highlight the urgency of addressing distraction in the context of the digital age and provide practical recommendations for individuals, platforms, and policy makers to foster healthier and more focused media environments.

***Keywords:*** Attention, media platform, AI algorithms, gender differences, digital behavior

## 1. Introduction

In this new era, the way humans acquire and process information has undergone a transformation—traditional paper-based reading has been replaced, while visual methods of obtaining information, such as short videos and self-media, have become widely adopted. The AI system on the platform can be used to understand users' preferences, recommend relevant content and videos, and provide immersive information. Users no longer need to search actively. This behavior has led to an increasingly serious problem of attention scarcity [1]. Fragmented high-frequency input disrupts cognitive patterns and weakens the ability to remain focused in learning, working and other tasks [2].

Attention is a cognitive function that plays a crucial role in academic performance, work efficiency and mental health. However, most of the existing studies focus on a single variable, such as media usage time, content preferences or psychological characteristics [3]. Few people have attempted the comprehensive modeling method that combines the technical, psychological and behavioral dimensions. Furthermore, gender differences - a potential mitigating factor - are often overlooked. This study addresses this gap by investigating how AI-driven short-video platforms and digital media behaviors affect concentration levels, with a focus on gender-based influences.

This scientific research paper reviews theoretical and empirical literature, and then conducts a multiple regression analysis based on the survey data. Then subgroup analysis was conducted by gender. Finally, this study put forward targeted suggestions at the individual, platform and policy

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levels, and summarized contributions and future research directions. provided by Microsoft Word if they are not familiar with how to apply styles.

## 2. Literature review

### 2.1. Definition and classification of concentration

Attention refers to the individual's purposeful selection of specific objects and tasks, or the cognitive ability to concentrate mental resources, and is one of the core mechanisms in the human information processing and processing system [4]. This ability is a prerequisite for many complex tasks, including learning, working, reading, and the like, and is an important part of maintaining memory, controlling behavior, and regulating emotions.

There are four main types of Attention: Selective Attention, Sustained Attention, Alternating Attention, Divided Attention [5]. Selective Attention refers to the ability to focus on one of the multiple interference choices for processing, helping an individual to shield from other disturbances. Focus on more important and critical information; Sustained Attention means to maintain a sustained attention for a long time and complete tasks such as deep reading and writing. Alternating Attention means switching attention efficiently and quickly between different tasks. Divided Attention is the ability to process multiple pieces of information or tasks at the same time. Research in recent years has shown that high-frequency fragmented content, such as short videos, can reduce Selective and Sustained Attention, Moreover, frequent switching between different characters may interfere with the ability of Alternating Attention [3].

### 2.2. Definition of media environment

With the rapid development of the Internet, the way of information dissemination has gradually changed from linear text to fast-paced content presentation mainly based on vision. Short video and self-media platforms have gradually emerged in this context and become the main channels for the public to obtain information and have entertainment [2]. Short-video platforms like Tiktok and Kuaishou usually offer content ranging from 15 seconds to 5 minutes. Most push systems that rely on AI algorithms conduct personalized and precise push based on users' browsing habits, increasing users' stay and usage time. Self-media platforms allow any user to create and post content, such as Rednote and Zhihu. It is also through the algorithmic recommendation mechanism that the content is made more personalized and immersive. Both share common characteristics, such as fragmented information, high-frequency social interaction, algorithmic preference for push notifications, and frequent cross-platform transitions.

### 2.3. Comprehensive factors affecting human concentration

#### 2.3.1. Self-media platforms

Current research indicates that in the context of the rapid development of digital media, the dissemination mode of fragmented, fast-paced and highly socialized content has changed the pattern of individual attention resource allocation [2]. Overall, it affects concentration through fragmented information dissemination, social addiction behaviors, and the use of multi-platform switching tasks:

Firstly, the content of short videos generally falls within a certain time frame, emphasizing the rapid acquisition of pleasure and the quick transmission of information, which leads to frequent and superficial information input. According to research, long-term exposure to fragmented information can weaken an individual's sustained attention. When the brain is accustomed to short-term concentration of attention, it will be difficult to maintain several states for a long time [6].

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Secondly, the human dopamine secretion mechanism can be stimulated through behaviors such as liking, commenting, and sharing on the platform, creating a psychological dependence for users in social feedback. The pleasant feeling generated by this kind of behavior may interrupt the process of deep thinking and processing information, and there is a greater tendency to frequently switch the focus object, thus making it difficult to handle a single piece of information [7].

#### 2.3.2. AI recommendation algorithm mechanisms

Artificial intelligence recommendation systems are an important driving force for self-media platforms, enhancing platform stickiness and also having an impact on concentration [6,8]. This kind of recommendation prolongs the usage time of users, causes individuals to form unconscious dependent behaviors, weakens the ability to filter information, and reduces the opportunities for self-regulating attention [9]. Meanwhile, the recommended content is highly consistent, resulting in increasingly homogeneous information received by users, reducing the diversity of cognitive stimuli, declining the brain's ability to process information, and weakening cognitive flexibility [10]. Also, because it is necessary to capture users' attention in a short time, the content of short videos is more radical (exaggerated, stimulating, and dramatic). This may lead to a decrease in users' patience for some calm and low-stimulation tasks (reading, writing), resulting in problems with concentration [2].

#### 2.3.3. Psychological factors

Emotional fluctuations, including anxiety, depression and low spirits, can significantly weaken the ability to concentrate and reduce cognitive ability [3]. Self-control is also one of the factors to be considered. High self-control can help individuals resist external distractions and maintain concentration.

#### 2.3.4. Physiological and behavioral factors

The quality of sleep and the acquisition of nutrition are important conditions for the operation of the cognitive system. Studies have pointed out that long-term sleep deprivation can affect the processing and response speed of events and memories, as well as the control of attention by the prefrontal cortex [4]. Dietary structure is also one of the very important factors. Excessive intake of sugar-oil mixtures can reduce attention fluctuations. On the contrary, consuming foods rich in omega-3 can help improve sustained attention. Meanwhile, lack of exercise can also reduce the level of concentration.

#### 2.3.5. Environmental factors

The external environment, such as noisy background noise, shared Spaces among multiple people, and frequent social interruptions, can make concentration difficult, disrupt the state of concentration, and affect the continuity of cognition [4].

#### 2.3.6. Group differences factors

The characteristics of concentration among different groups of people also vary. Teenagers' attention is more likely to be disturbed by the media. However, the middle-aged and elderly groups have a natural decline in the speed of processing information and the breadth of their attention.

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## 3. Analysis

### 3.1. Comprehensive linear regression model

In the initial stage of the analysis, the collected data are used to construct a multiple linear regression model. The model aims to examine the influence of several independent variables on the dependent variable, attention level (Y).

The variables involved are listed in the Table 1:

Table 1: Independent variable (X) and dependent variable (Y)

| Variable Name | Variable Symbol | Description |
|---|---|---|
| Interaction Behavior | X1 | Frequency of user interactions on video platforms (likes, comments, shares) |
| Recommendation System | X2 | Degree to which algorithmic content recommendations influence user behavior |
| Depressing Level | X3 | Level of how people feel pressure and frustrated |
| Exercise Frequency | X4 | Frequency of physical activity (number of times per week) |
| Noise Environment | X5 | Level of background noise in the user's daily environment |
| Dietary Habits | X6 | Healthiness of diet |
| Self-Control Ability | X7 | Individual's capacity to regulate behavior and emotions |
| Concentration Level | Y | Measured level of sustained focus during tasks |

The structure of the model is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon \tag{1}$$

Without correcting heteroscedasticity, the results of the linear regression model are shown in the Table 2 below.

Table 2: Linear regression results (uncorrected for heteroskedasticity)

| Variables | Coef (B) | Std. Error | t-value | p-value | Sig |
|---|---|---|---|---|---|
| $X_1$ | 0.369 | 0.052 | 7.137 | <0.001 | *** |
| $X_2$ | 0.388 | 0.054 | 7.207 | <0.001 | *** |
| $X_3$ | -0.091 | 0.069 | -1.310 | 0.191 | |
| $X_4$ | 0.048 | 0066 | 0.734 | 0.464 | |
| $X_5$ | -0.019 | 0.062 | -0.303 | 0.762 | |
| $X_6$ | 0.170 | 0.069 | 2.458 | 0.015 | ** |
| $X_7$ | -0.066 | 0.073 | -0.908 | 0.365 | |
| Constant | 0.867 | 0.286 | 3.035 | 0.003 | ** |

***p < 0.01, **p < 0.05, *p < 0.1

Based on the regression results, the estimated equation can be expressed as:

$$Y = 0.87 + 0.37X_1 + 0.39X_2 - 0.09X_3 + 0.05X_4 - 0.02X_5 + 0.17X_6 - 0.07X_7 + \varepsilon \tag{2}$$

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The INTERACTION coefficient is 0.369 and the standard error is 0.052. This implies that, holding all other variables constant, a one-unit increase in interaction activities on short video platforms is associated with a 0.369-unit increase in concentration level. The p-value is less than 0.001, so it is statistically significant. Similarly, the coefficient of RECOMMENDATION is 0.388, and the p-value is less than 0.001, indicating that a more favorable perception of algorithmic recommendation significantly improves attention. Diet was also significantly positively correlated with attention (B = 0.170, p-value = 0.015), indicating that healthy dietary habits may contribute to the enhancement of attention, but in terms of comparative influence, it was not higher than INTERACTION and RECOMMENDATION. In contrast, DEPRESSION, SPORTS, NOISE and SELF-CONTROL are not significant predictors of concentration levels in this model. Although these predictors do not reach statistical significance ($p > 0.05$), they remain theoretically important based on existing cognitive and behavioral research, and may exhibit stronger effects under different modeling conditions or larger sample sizes. Overall, this model explains approximately 48% of the concentration level variance, and all the assumptions of linear regression (normality, mean square error, independence) are reasonably satisfied (as shown in Figure 1, Figure 2 and Figure 3).

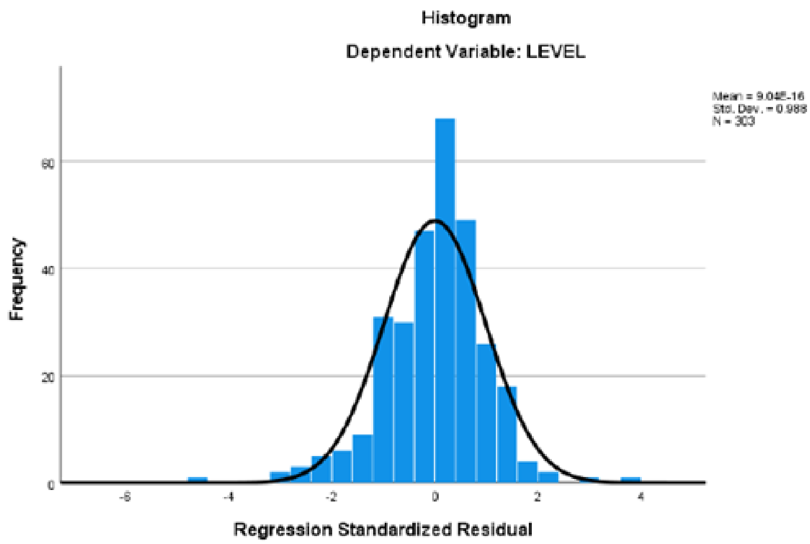


Figure 1: Histogram of standardized residuals

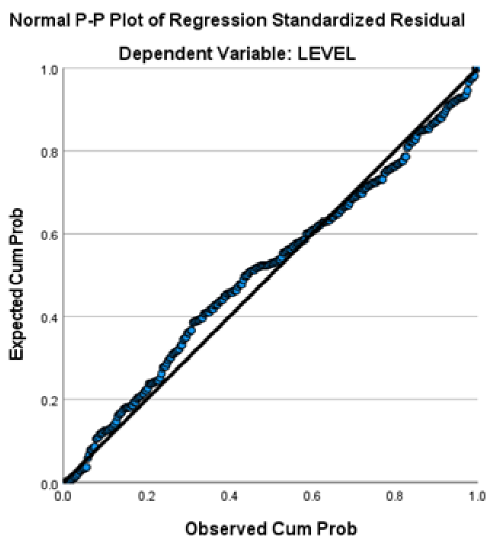


Figure 2: Normal P-P plot of standardized residuals

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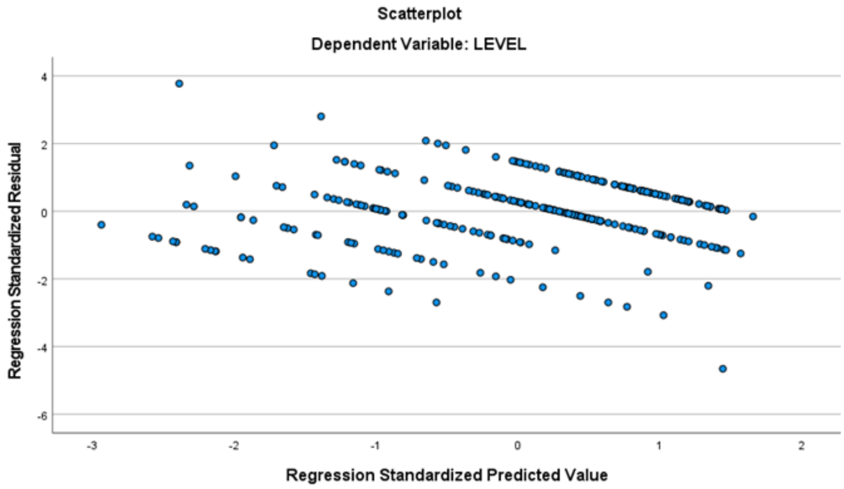


Figure 3: Scatterplot of standardized residuals versus predicted values

## 3.2. Concentration and gender: comparative analysis

To study the gender differences in the dependent variable of concentration level, regression linear analyses were conducted for male and female participants respectively.

Table 3: Comparison of regression model fit indices by gender

| | MALE (gender = 1) | FEMALE (gender = 2) |
|---|---|---|
| R Squared | 0.508 | 0.493 |
| Adjust R squared | 0.485 | 0.467 |
| ANOVA p-value | 0.000 | 0.000 |
| Durbin-Watson | 1.930 | 2.085 |

As shown in Table 3, the adjusted R*2 for the male model was 0.485, indicating that approximately 48.5% of the variance in attention levels could be explained by the given factors. Similarly, the adjusted R*2 of the female model was 0.467, explaining approximately 46.7% of the variance. Both models have very good adaptability to the model, as shown by the significant F-test ($p<0.001$) and the Durbin-Watson statistic close to 2, indicating that there is no serious autocorrelation problem.

Table 4: Significant predictors of attention level among male participants

| | β | Significance |
|---|---|---|
| INTERACTION | 0.382 | 0.000 |
| RECOMMENDATION | 0.393 | 0.000 |
| Others (DEPRESSING, SPORTS, NOISE, DIET) | Not significant (p-value > 0.05) | - |

From the Table 4, for male participants, the two dependent variables, INTERACTION ($\beta=0.382$, $p<0.001$) and RECOMMENDATION ($\beta=0.393$, $p<0.001$), have significant positive predictive associations for the level of concentration. Specifically, participating more in social interaction on short-video platforms is more favorable to artificial intelligence recommendation systems and is associated with a higher level of concentration. Other variables, including depression, exercise participation, noise exposure, dietary habits and self-control, could not significantly predict the concentration of male participants ($p < 0.05$).

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Table 5: Significant predictors of attention level among female participants

| | β | Significance |
|---|---|---|
| INTERACTION | 0.376 | 0.000 |
| RECOMMENDATION | 0.372 | 0.000 |
| SELF-CONTROL | -0.188 | 0.036 |
| Others (DEPRESSING, SPORTS, NOISE, DIET) | Not significant (p-value > 0.05) | - |

For female participants from Table 5, similar patterns were observed: INTERACTION ($\beta=0.376$, $p<0.001$) and RECOMMENDATION ($\beta=0.372$, $p<0.001$) positively affected the concentration. However, compared with men, SELF-CONTROL ($\beta= -0.188$, $p=0.036$) became a significant negative predictor in women. This discovery indicates that the higher level of self-control in women may be related to a decline in self-measured concentration.

It is notable that previous studies have shown that high participation in short-video platforms may impair objective attention and cognitive control. Therefore, the observed positive relationships may reflect self-perception bias rather than true cognitive improvement.

# 4. Suggestion

## 4.1. Personal level

First of all, as an individual, one needs to develop the habit of training and extending the duration of attention in daily life. Stable and in-depth concentration can be established by deeply concentrating on a specific period of time, such as techniques like the Pomodoro Technique.

Meanwhile, the use of media platforms should be more reasonable. Intervention can be achieved by controlling the usage duration, turning off push notifications, and reducing the frequency of passively receiving information.

In addition, maintaining a healthy daily routine is also very important, including ensuring adequate sleep and persisting in regular physical exercise. This can help enhance the executive function of the brain, improve self-control ability, and thereby indirectly increase attention levels.

## 4.2. Enterprise level

As important constructors and maintainers of the media environment, enterprises and platforms should take on corresponding social responsibilities.

First, in designing AI recommendation algorithms, platforms can introduce mechanisms such as usage time reminders to encourage users to manage their media consumption more reasonably. While such measures may reduce user stickiness and advertising revenue in the short term, they are beneficial for building a healthier and more sustainable digital ecosystem in the long run.

Second, platforms can develop a focus mode or simplified interface—such as disabling push notifications and adding time-based usage alerts—to reduce passive environmental distractions and support users in maintaining concentration.

## 4.3. Government level

The government also plays a key role in maintaining public perception. First of all, Media Use Education courses should be offered during adolescence to cultivate good media use habits and attention management skills from an early age. Secondly, legislation and supervision over the application of self-media platforms and recommendation algorithm technologies should be

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strengthened. Policies should manage the transparency of AI algorithms, limit overly immersive content frameworks and bottom lines, and protect users' cognitive autonomy.

## 5. Conclusion

This study takes self-media platforms and AI recommendation algorithms as the entry points to explore the multi-dimensional influence mechanisms they have on human concentration. By reviewing the existing literature and summarizing multiple factors such as psychology, physiology, behavior and technology, this study points out that fragmented information dissemination, social addiction mechanisms, personalized recommendation algorithms, etc. are important paths leading to the decline of concentration.

Although this study has systematically sorted out the influencing mechanism of concentration, there are still certain limitations. For example, the data analysis part is mainly based on the induction of existing literature, lacking empirical investigation and experimental verification. Also, the assessment of concentration might only be the participants' own evaluation level and not a more accurate result.

Future research can pay more attention to - examining the changing trend of concentration through longitudinal tracking studies and revealing causal relationships; Randomized controlled trials (RCTS) were designed to examine the improvement effects of different intervention methods (such as digital withdrawal and meditation training) on concentration; Expand the diversity of samples and compare the similarities and differences in attention mechanisms among individuals with different social backgrounds and media literacy levels.

## References


[1] *White, D. J. (2024) Paying Attention to Attention: Psychological Realism and the Attention Economy. Synthese (Dordrecht), 203, 43.*

[2] *Park, J. and Jung, Y. (2024) Unveiling the Dynamics of Binge-Scrolling: A Comprehensive Analysis of Short-Form Video Consumption using a Stimulus-Organism-Response Model. Telematics and Informatics, 95, 102200.*

[3] *Hou, Z., Ma, K., Wang, Y., Yu, J., Ji, K., Chen, Z. and Abraham, A. (2021) Attention-Based Learning of Self-Media Data for Marketing Intention Detection. Engineering Applications of Artificial Intelligence, 98, 104118.*

[4] *Guo, R. and He, Q. (2023) Art Education on Students' ADHD in the Era of Self-Media. CNS Spectrums, 28, S77-S77.*

[5] *Gong, J., Zanuddin, H., Hou, W. and Xu, J. (2022) Media Attention, Dependency, Self-Efficacy, and Prosocial Behaviours during the Outbreak of COVID-19: A Constructive Journalism Perspective. Global Media and China, 7, 81-98.*

[6] *Gau, J. M., Paoline, E. A. and Paul, N. D. (2022) De-Policing as a Result of Public Scrutiny: Examining Officers' Perceptions of Negative Media Attention and Willingness to Engage in Self-Initiated Activity. Journal of Crime & Justice, 45, 539-551.*

[7] *Qu, M. (2022) Automatic Generation of News Commentary on Social Media Based on Self-Attention Mechanism. Wireless Communications and Mobile Computing, 2022, 1-8.*

[8] *Hendrickx, J. and Ranaivoson, H. (2021) Why and how Higher Media Concentration Equals Lower News Diversity – the Mediahuis Case. Journalism (London, England), 22, 2800-2815.*

[9] *Knuth, I., Petzold, T. and Richter, F. (2025) Digital Transformation's Impact on Media Concentration and News Diversity: A Network Analysis of Cross-Platform News Usage in Germany. Journal of Media Economics, 37, 4-19.*

[10] *Zhang, M., Hou, J., Xia, J., Zeng, Y. and Miao, L. (2023) Influences of Input Concentration, Media Particle Size, Metal Cation Valence, and Ionic Concentration on the Transport, Long-Term Release, and Particle Breakage of Polyvinyl Chloride Nanoplastics in Saturated Porous Media. Chemosphere (Oxford), 322, 138130-138130.*