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Do social motivations predict addiction to social media in young people? The role of flow and algorithm awareness

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Título: ¿Las motivaciones sociales predicen la adicción a las redes sociales en los jóvenes? El papel del flujo y la conciencia algorítmica.
Resumen: El uso adictivo de las redes sociales se ha convertido en un fenómeno cada vez más relevante entre los jóvenes, afectando tanto a su bienestar psicológico como a su comportamiento online. El objetivo principal de este estudio es investigar las asociaciones entre el uso adictivo de las redes sociales, las motivaciones de uso, el flujo y el conocimiento de los algoritmos. Nuestra hipótesis es que la experiencia de flujo y la conciencia del algoritmo son dos mediadores a través de los cuales motivaciones sociales relevantes influyen en el desarrollo de una adicción a las redes sociales. Se utilizan cuestionarios validados para medir las variables del estudio, incluido el BSMAS para evaluar la adicción a las redes sociales. El modelado de ecuaciones estructurales (SEM) con pruebas Bootstrap se utiliza para analizar los datos recopilados de una muestra de 580 usuarios más jóvenes de entre 18 y 22 años en China (M = 20.61, SD = 1.32), con un 47.7% de mujeres y un 52.2% de hombres, todos estudiantes de pregrado, con el fin de probar las hipótesis de investigación. Los resultados revelan que diferentes mecanismos de adicción implican diferentes asociaciones con motivaciones socialmente relevantes. Avanza en el campo de la adicción a las redes sociales al mostrar que la adicción también está relacionada con la conciencia de algoritmos, a través del cual se identifica un nuevo mecanismo alternativo de adicción.
Palabras clave: Adicción. Conciencia de algoritmos. Fluir. Modelo de ecuaciones estructurales. Motivación social. Usuario de redes.

Abstract: Addictive use of social media has become an increasingly relevant phenomenon among young people, affecting both their psychological well-being and their online behavior. The principal objective of this study is to investigate the associations between addictive use of social media, usage motivations, flow, and algorithm awareness. Our hypothesis is that the flow experience and the algorithm awareness are two mediators through which relevant social motivations influence the development of an addiction to social media. Validated questionnaires are used to measure the study variables, including the BSMAS to assess social media addiction. Structural equation modeling (SEM) with Bootstrap tests is used for analyzing data that is collected from a sample of 580 younger users aged 18 to 22 in China (M = 20.61, SD = 1.32), with 47.7% women and 52.2% men, all undergraduate students, in order to test the research hypotheses. The results reveal that different addiction mechanisms implicate different associations with socially relevant motivations. It advances the field of addiction to social media by showing that addiction is also related to algorithm awareness, through which a new alternative mechanism of addiction is identified.
Keywords: Addiction. Algorithm awareness. Flow. Model of structural equations. Social Motivation. Networks user.

Introduction

The rise of social media has profoundly transformed how we interact and consume content, becoming a global social phenomenon. However, as with other popular activities, concerns have also emerged regarding potential addiction to these platforms, particularly among adolescents and young adults. These users are especially vulnerable to developing an addiction due to their tendency to constantly check notifications, consume content, and create new videos (Carbonell et al., 2012; Longobardi et al., 2020; Yang et al., 2022).

Moreover, the personalization algorithms on these platforms often filter and prioritize content that is appealing to users, typically aligning with their existing preferences and perspectives. This can restrict the diversity of information users are exposed to, potentially contributing to an addictive cycle (Cho et al., 2020). Over time, excessive social media use can result in negative consequences such as decreased concentration, reduced productivity, and increased mental health issues, including depression and anxiety (Bérail et al., 2019; Wu, 2022).

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To counter these risks, experts suggest simple measures like moderating usage, taking breaks, and limiting notifications—strategies that can effectively prevent addiction (Echeburúa, 2010; Vanman et al., 2018). While social media can indeed be a source of creativity and entertainment (Abdelfattah et al., 2022), responsible use is essential to mitigate its potential addictive effects. Understanding the mechanisms that drive excessive use will allow for a better comprehension of its effects and enable the development of more targeted interventions to mitigate the addictive impact of these platforms.

UGT and social motivations

The gratifications of needs comprise of social interaction with other people to gain a meaningful and important experience, positive experiences of emotions, self-confidence, social integration, and awareness and perception of different issues, cultures, and developments (Katz et al., 1973). Previous studies applying uses and gratifications theory (UGT) to social media platforms indicate that the gratifications people seek differ based on the specific platform and its usage (Kircaburun et al., 2020). Thus, UGT has been successfully applied to various social media platforms including Facebook (Dhir et al., 2015; Raza, et al., 2022; Seidman, 2013), YouTube (Sokolova and Perez, 2021; Khan, 2017), TikTok (Fiallos-Ordoñez et al., 2021; Wang et al., 2023), Instagram

(Huang and Chang, 2020; Menon, 2022) and Snapchat (Phua et al., 2017; Meshia et al., 2020).

At first, the theory concentrated on five primary gratifications experienced from the use of media, from information and entertainment to social interaction, personal identity and escape from daily life (Croes and Bartels, 2021). For instance, users often engage in passive activities like watching and liking or disliking videos on YouTube primarily for relaxation and entertainment, whereas commenting and uploading videos are driven by the desire for social interaction (Khan, 2017).

Socially relevant motivations such as information and social interaction are mainly related to interacting and connecting with friends or social media influencer (You & Hon, 2022) and maintaining social ties (Alhabash and Ma, 2017). Social media are used to seek and share relevant notices and information about others and society and help maintain interpersonal relationships or parasocial relationships (Cohen and Holbert, 2021; Muntinga et al., 2011), thus helping them to satisfy their need to belong. Moreover, the social media use can help users communicate and interact with others in order to maintain social relationships. A distinction can be made between social attention, focused social interaction, routine impersonal interaction, and unfocused interaction (Hall, 2018).

Social media addiction

Studies report that younger individuals tend to score higher on social media addiction scales compared to older individuals (Kuss et al., 2014). In addition, it is suggested that individuals who are not in relationships are more prone to developing addictive social media usage (Kuss et al., 2014). During the covid-19 epidemic, many adolescent users in confinement perceived greater addiction when using the internet and social media platforms (Fernandes et al., 2020).

According to the specific criteria for distinguishing between the addictive and the non-addictive use (Griffiths, 2005), the addictive use of social media should be manifested by the preoccupation with social media, the use of social media to reduce negative feelings, the steady increase in social media use to obtain the same pleasure from them, the bearing of distress when not allowed to use social media, the sacrifice of other obligations and/or loss of other important life areas due to the social media use, and the fail to control the social media use. On the other hand, it could be differentiated between excessive but healthy usage and maladaptive behaviors, and it is pointed out that the increased time that is spent online do not indicate maladaptive social media use (Griffiths et al., 2014) and the frequent and excessive social media use in an unproblematic way clearly wouldn't create an addiction (Stanculescu et al., 2022). The literature on social media addiction has also noted the presence of comorbidities, such as depression (Cheng et al., 2022; McCrae et al., 2017), anxiety (Cheng, et al, 2023; Wei et al., 2024) and stress (Ardèvol-Abreu et al., 2022; Marino et al., 2017).

Flow

Flow experience or flow can be defined as a mental state of full involvement in something, forgetfulness of time, constant exhaustion and everything outside of the activity itself (Csikszentmilhayi, 2014). By experiencing the flow, a loss of anxiety and a distorted perception of time are realized. The flow state is inherently pleasurable and involves a reduction or loss of self-awareness (Hoffman and Novak, 2009). In this state, time can appear to remain immobile while one that is immersed in a consumption event has the intrinsic motivation for repeating an activity continuously (Csikszentmihalyi, 1997).

The dimensions directly related to social media are investigated. For example, the Facebook flow consists of five constructs: focused attention, which refers to the high attention and focuses on the use of Facebook; enjoyment, which refers to the enjoyment and pleasure/fun that are generated by the use of Facebook; curiosity that refers to the desire to discover the news and notices on Facebook; telepresence that refers to the sensation of immersing yourself in a world created by Facebook; distortion of time that refers to the loss of the sense of time while using Facebook (Brailovskaia et al., 2018).

The flow has played a crucial role in understanding online behavior and explaining the stimulating online experiences nature (Peleta et al., 2017). Gratifications associated with interaction with other users or with platform content have been confirmed to influence the online flow experience (Huang et al., 2014). Therefore, the following hypotheses are proposed:

H1. Information positively influences flow experience.

H2. Social interaction positively influences flow experience.

Furthermore, previous studies hypothesized that the flow may function as a precursor to internet and social media addictive behaviors (Anderson et al., 2016; Brailovskaia et al., 2022). Thus, it is assumed that young people who experience more online flow have a higher risk of internet addiction (Stavropoulos et al., 2013; Wang et al., 2020). As a result, the following hypothesis is proposed:

H3. Flow experience positively influences social media addiction.

Algorithm recommendation and algorithm awareness

Artificial intelligence is used with the automatic algorithm to personalize what the user consumes through the search and its recommendations and show the user the content that may be of interest, creating addiction in the process of using the software. Algorithms tailor its service at an individual level on the basis of the demographics, the online behaviors and preferences, the activities of friends and social connections, and a host of factors that are not known (Rassameeroj and Wu, 2019). In this context, the users interact with these personalized platforms, and feed the system with more data from which the personalization can be further improved (Cho et al., 2020; Lim et al., 2022). In this context, algorithm awareness, defined as the acknowledgment of algorithms' presence and functioning in online content (Swart, 2021), is essential. Greater access to information about how these algorithms work can help users better understand their impact. Consequently, the following hypotheses are formulated:

H4. Information positively influences algorithm awareness.

H5. Social interaction positively influences algorithm awareness.

Several researchers in the field of journalism and communication are worried about the negative impacts of algorithmic mediation, where users interact trapped in filter bubbles (Rodríguez, 2017), and the decline of cognitive democracy as a result of automatic content personalization, especially with prior censorship and illicit trafficking of personal information (Bajaña, 2021). In particular, young people, who still lack knowledge of digital technologies, tend to access precarious and limited varieties of information (Quelhas-Brito, 2012).

Algorithm awareness, which arises from experience, has been linked to frequency of use and exposure, active or passive use, adjustment of settings, and deductive and inductive reasoning (Eslami et al., 2015). It has been noted that young users still do not understand or ignore the logic behind the functioning of algorithms on social networks, increasing the risk of overexposure and addiction or dependence on social media applications (Gómez et al., 2021). In this regard, Wang and Guo (2023) have demonstrated that greater algorithm awareness can enable users to identify how algorithms influence their behavior, promoting greater control over their time and use of social networks. Thus, the following hypothesis is suggested:

H6. Algorithm awareness negatively influences social media addiction.

Finally, algorithm awareness may also influence the flow experience on social media, reducing its intensity. When users understand how algorithms select content to maximize their time on the platform, this knowledge can disrupt the sense of total immersion or loss of time that social networks aim to induce (Bucher, 2016). Based on this, the following hypothesis is established:

H7. Algorithm awareness negatively influences flow experience.

Indirect Effects

When users receive personalized information based on their interests, it promotes a flow state which, by satisfying their need for immersion, can increase the risk of developing addictive behavior (Brailovskaia et al., 2022). In this sense, information acts as a precursor that, by facilitating the flow experience, indirectly influences addiction. Similarly, social interaction on digital platforms reinforces this flow state by fulfilling the need for connection and belonging (Huang et al., 2014), which can also lead to addictive behaviors, mediated by this immersion. Furthermore, previous research indicates that motivation as escapism indirectly but positively affects TikTok addiction by enhancing the flow experience (Miranda et al., 2023). Consequently, the following hypotheses are put forward:

H8. Information positively influences addiction indirectly through flow experience.

H9. Social interaction positively influences addiction indirectly through flow experience.

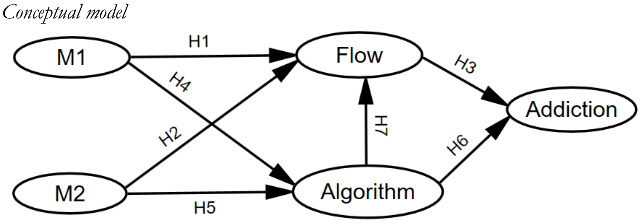
Algorithm awareness may also play a crucial role in the relationship between social media use and addiction. A recent empirical study demonstrates that the fear of missing out on important information exerts an indirect effect on compulsive social media use through algorithm awareness, which acts as a mediator that reduces this influence (Wang & Shang, 2024). In this sense, the perception that algorithms control the information they see increases this awareness, reducing the likelihood of addictive behaviors. Similarly, social interaction may also influence awareness of the role of algorithms, promoting more conscious and controlled use, which reduces the tendency toward addiction. In this regard, the subsequent hypotheses are suggested:

H10. Information negatively influences addiction indirectly via algorithm awareness.

H11. Social interaction negatively influences addiction indirectly via algorithm awareness.

Based on the proposed hypotheses, the conceptual model for the research is presented (Figure 1).

Figure 1
Conceptual model



Methods

Participants

Participants were recruited in Novembre of 2023 through a professional Chinese online research firm (https://www.sojump.com). It features a substantial panel sample of over 260 million participants in China. Quota sampling on the basis of age and education was used to allow the sample to represent young people aged 18 to 22 (M = 20.61, SD = 1.32) who were studying for a bachelor's degree. Finally, 580 responses were collected with 47.7% female and 52.2% male, closely resembling the Chinese demographic distribution.

Measures

Regarding the instrument used, the motivation scales employed in the current study were based on previous research on the motives for using Instagram (Sheldon and Bryant, 2016) and those adapted from TikTok (Omar and Dequan, 2020). These scales were rated on a 5-point Likert scale, from 'very unlikely' (scored as 1) to 'very likely' (scored as 5), in order to understand user engagement and consumption. The scales were developed from a series of questions that demonstrated good reliability, with all Cronbach's alphas exceeding 0.7.

To assess the severity of social media addiction, we utilized the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2017). It consisted of six items based on the main characteristics of addictive social media use and was rated on a 5-point Likert scale (1 = very rarely, 5 = very often). In the present study, a Cronbach's alpha of 0.85 was calculated, which evidenced good internal consistency for the BSMAS with our sample.

We measured the flow experience of social media using the Brailovskaia et al. (2018) flow questionnaire. This instrument consisted of eleven items (e.g., "While using social media, the world generated by the sites I visit is more real for me than the real world") that were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The Algorithmic Media Content Awareness (AMCA) scale that was developed by Zarouali et al. (2021) was adopted, to measure the awareness of algorithm that works in the content selection and presentation on social media. The AMCA scale has been used for assessing successfully the algorithm awareness of three online platforms such as Netflix, YouTube and Facebook. The scale consisted of 13 items that specifically measure the level of awareness of the users about the use of algorithms with four factors such as content filtering, automated decision making, human-algorithm interaction, and ethical considerations. Each of the factors included items that indicated the role that algorithms played in media content presentation (for example, algorithms are used to prioritize certain media content above others). The possible responses ranged from 1 (not at all aware) to 5 (completely aware).

Data analysis

IBM SPSS 26.0 and AMOS 26.0 were used for the statistical analysis. Initially, descriptive analyses were conducted using SPSS to obtain descriptive statistics of the participant sample. Among these, the BSMAS scale was specifically used to assess the severity of social media addiction, due to its relevance to the study's objectives. The descriptive results are presented alongside the correlation analysis to facilitate the joint interpretation of the relationships between the variables.

Structural Equation Modeling (SEM) was carried out with a two-step method (Anderson and Gerbing, 1988). In the first stage, a Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the constructs, highlighting social motivations due to their fundamental role as drivers of behavior on social networks. Subsequently, the Pearson correlation coefficient was used to examine associations between the variables. Once the measurement model was confirmed, the structural model was used to test the study’s hypotheses, evaluating the causal relationships between the latent variables and both direct and indirect effects.

For the latter, the Bootstrap method was applied with 2,000 samples and a 95% bias-corrected confidence interval. An indirect effect is considered significant at the 0.05 level if the 95% confidence interval does not contain 0; if it includes 0, the indirect effect is not statistically significant at this level (Byrne, 2013).

Results

Measurement model

An exploratory factor analysis (EFA) was conducted in SPSS 26.0. Table 1 shows that there were no concerns about the validity and reliability for the measures of the social motivations. First, all the items measured had satisfactory loadings (> .70) and AVE (> .50), which indicated good convergent validity. Second, the Cronbach's Alpha and CR of each variable (> .70) revealed that all measurement items were internally reliable.

Table 1
AFE results on the social motivations

Motivations and items	Loading	α
Motivation 1: Information		0.87
To get information about things that interest you.	.76	
To keep up with news and current events.	.77	
To provide others with information.	.85	
To share information about your life and interests with other people.	.79	
Motivation 2: Social interaction		0.84
To interact with several people.	.77	
To build and maintain good relationships with others.	.80	
To connect with people who share some of your values.	.73	

Table 2 provides the Pearson's correlations, as well as the means and standard deviations of the main variables. In general, information (M = 4.17; SD = .67) and social interaction (M = 3.97; SD = .72) were the important social motivations among young people. Flow (M = 3.70; SD = .55) was high while algorithm awareness (M = 3.41; SD = .48) and social media addiction (M = 3.48; SD = .67) were relatively high. Furthermore, both social motivations were positively correlated with flow, algorithm awareness, and social media addiction. Moreover, there was a relationship between algorithm awareness and addiction and a relationship between flow and addiction, but there was no relationship between flow and algorithm awareness, so the hypothesis 7 was thus rejected.

Table 2
Descriptive statistics and correlation analysis (n = 580)

Variables	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Sex	-	-	-						
2. Age	20.61	1.32	.00	-					
3. Information	4.17	.67	.06	.03	-				
4. Social interaction	3.97	.72	-.12	.04	.60*	-			
5. Flow	3.70	.55	-.10	-.03	.50*	.58*	-		
6. Algorithm awareness	3.41	.48	.00	-.05	.48*	.38*	.15	-	
7. Social media addiction	3.48	.67	-.04	-.03	.32*	.34*	.67*	.18*	-

Note: $*p < .05$

Among them, the BSMAS was used to assess the severity of the social media use addiction. Table 3 accurately indicates the analyzed data that represented the mean and standard deviation. The following items "Feel an urge to use social media more and more " (M = 3.60; SD = 0.76) and "Spend a lot of time thinking about social media or plan use of social media" (M = 3.55; SD = 0.92) received higher scores (means).

Table 3
Social media addiction

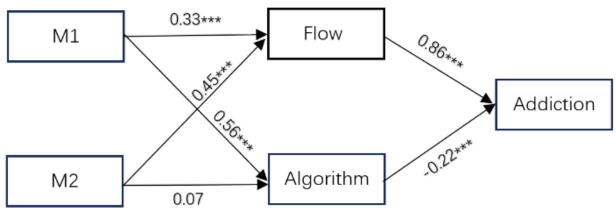
	M	*SD*
1. Spend a lot of time thinking about social media or plan use of social media.	3.55	.92
2. Feel an urge to use social media more and more.	3.60	.76
3. Use social media in order to forget about personal problems.	3.30	.97
4. Try to cut down on the use of social media without success.	3.49	.89
5. Become restless or troubled if you have been prohibited from using social media.	3.40	.98
6. Use social media so much that it has had a negative impact on your job/studies.	3.51	.97

Analysis of the mediation model

SEM analysis with SPSS AMOS 26 was conducted to analyze the hypothesized mediation effects (see Fig. 2). The insignificant relationship between algorithm awareness and flow variables in the path model was then removed in order to obtain a simpler model. The fit of the path model was assessed: χ^2 (202) = 248.64, $p < .001$, $\chi^2/df = 1.23$, GFI (goodness-of-fit index) = .97, CFI (comparative fit index) = .97, RMSEA (root mean square error of approximation) =.02, TLI (Tucker-Lewis index) = .96. These indices revealed that the path model had a good fit for the data.

Bias-corrected Bootstrap method of 95% confidence interval (CI) with 2000 resamples was used to examine the mediating effects (Table 4). If the 95% CI do not include zero, then the effect is considered significant. The results showed that the direct effects of information on flow (effect = .33, 95% CI = [.02,.66]) and on algorithm awareness (effect = .56, 95% CI = [.18, .95]) were both significant, while its indirect effect on addiction via flow was also significant (effect =.28, 95% CI = [.03, .70]) and its indirect effect on addiction via algorithm awareness was negatively significant (effect = - .13, 95% CI = [- .36, - .01]). The hypotheses 1, 4, 8 and 10 were thus accepted. On the other hand, the direct effect of social interaction on flow (effect = .45, 95% CI = [.07, .72]) was significant and that on algorithm awareness (effect = .07, 95% CI = [- .31, .38]) was not significant, while its indirect effect on addiction via flow was significant (effect = .39, 95% CI = [.12, .65]) and its indirect effect on addiction via algorithm awareness was not significant (effect = - .02, 95% CI = [- .13, .06]). Therefore, the hypotheses 2 and 9 were thus accepted, but the hypotheses 5 and 11 were rejected. In addition, the direct effect of flow on addiction (effect= .86, 95% CI = [.65, .92]) was significant and high, while the direct effect of algorithm awareness on addiction (effect= - .22, 95% CI % = [- .43, - .04]) was significant and negative. Thus, the hypotheses 3 and 6 were accepted.

Figure 2
Structural equation model



Notes: *** $p < .001$.

Table 4
Bia-corrected bootstrap test in mediating effect with a 95% confidence interval

Model pathways			Effect	Lower	Upper
Direct path					
M1	→	Flow	.328	.021	.662
M1	→	Algorithm	.562	.178	.946
M2	→	Flow	.448	.074	.718
M2	→	Algorithm	.068	-.306	.376
Flow	→	Addiction	.861	.652	.917
Algorithm	→	Addiction	-.224	-.430	-.042
Indirect path					
M1 → Flow	→	Addiction	.282	.029	.696
M2 → Flow	→	Addiction	.385	.115	.645
M1 → Algorithm	→	Addiction	-.126	-.363	-.005
M2 → Algorithm	→	Addiction	-.015	-.128	.055
Total					
M1	→	Addiction	.157	.036	.447
M2	→	Addiction	.370	.110	.623

Discussion and Conclusions

From a theoretical perspective, this is the first study to evaluate both flow and algorithm awareness as mediating mechanisms underlying socially relevant motivating factors and the addiction to social media among young people. The survey results confirmed that algorithm awareness worked as an important mediator in the relationships between the specific motivations and the addiction. It also supported previous studies that had shown that the flow was a predictor of addiction to social networks (Brailovskaia et al., 2020; Khang et al., 2013).

As expected, we found significant and positive relationships between socially relevant motivations and the flow experience (H1, H2), which is consistent with previous studies (Huang et al., 2014; Miranda et al., 2023). Specifically, relevant information facilitates users' ability to focus and enjoy their activity on social media, while social interaction contributes to the sense of connection and engagement, further reinforcing the flow experience. These factors, working together, allow users to immerse themselves more deeply in the use of platforms, staying engaged and absorbed.

On the other hand, we confirmed that the flow experience is an important predictor of social media addiction (H3). Our results confirm that when users are immersed in this state of high concentration and enjoyment, they are more likely to develop addictive behaviors towards social media. This finding aligns with previous studies that highlight the close relationship between flow and addiction in digital contexts (Huang et al., 2014).

Additionally, we found that information has a positive and direct effect on algorithm awareness (H4). This suggests that users who receive and process more information on social media are more aware of how algorithms influence content visibility and selection. This finding supports the idea that exposure to information on these platforms increases users' ability to perceive the underlying algorithmic dynamics.

We found that social interaction had no direct effect on algorithm awareness (H5). Although previous research has indicated that interaction is a plausible variable related to content filtering and decision-making (Zarouali et al., 2021), this type of interaction should focus more on users'own behaviors on social media and human-machine interaction. Thus, no significant impact was found in our study.

This research found evidence that algorithm awareness plays an important role in reducing social media addiction (H6). Although the negative effect of algorithm awareness on addiction was moderate, our findings suggest that increasing knowledge about how algorithms function has the potential to significantly reduce addictive behaviors. Understanding how platforms use algorithms to select and prioritize content can empower users, helping them make more conscious and controlled decisions regarding their social media consumption.

Contrary to our expectations, we did not find a significant relationship between flow experience and algorithm awareness (H7). One possible explanation is that flow depends on total concentration on the task, with key factors such as challenge, clear objectives, and immediate feedback. Knowledge of the algorithms becomes secondary and does not interfere with the immersive experience.

Flow and algorithm awareness played the positive and negative mediating effects respectively between information and addiction to social media (H8, H10), and only flow played a positive mediating effect between social interaction and addiction to social media (H9). The hypothesis that social interaction indirectly but negatively influences addiction through algorithm awareness (H11) was rejected, although previous studies indicated that the interaction with algorithms on the basis of online behaviors analysis, demographics, and geographic data is becoming a common part of the digital media experience, and more social presence with human agency AI is perceived (Boerman et al., 2017; Liu, 2020).

This study makes important theoretical contributions by exploring the mediating role of algorithm awareness in the relationship between information exposure and social media addiction. Our findings suggest that algorithm awareness may play a key role in how users process information and manage their behavior on digital platforms. By examining this mechanism, the research expands the understanding of how knowledge of algorithms can influence the way users interact with content and, ultimately, their tendency to develop addictive behaviors. Additionally, we have identified that socially relevant motivations, such as information-seeking and social interaction, play a crucial role in the flow experience, which may deepen users' engagement with platforms.

This study also introduces a new perspective by investigating how the flow experience and algorithm awareness operate independently in the context of social media use. Our results challenge the common notion that awareness of algorithms directly affects users' immersion in the flow experience, suggesting that flow depends more on immersion in the activity than on conscious reflection about how content is managed. This opens new lines of inquiry into how other factors, such as selective attention or cognitive processing during flow, might influence the dynamics between immersion and awareness in digital environments.

From a practical perspective, our results highlight the importance of increasing users' knowledge of algorithms as a potential strategy to reduce social media addiction. Developing educational tools or more transparent interfaces could help users better understand the role of algorithms in shaping their experience, promoting more conscious and controlled use of platforms. Future research should focus on how algorithm awareness varies across different platforms and types of users, as well as on identifying more effective strategies for enhancing algorithm literacy. Additionally, it would be valuable to examine how other psychological factors, such as anxiety or user satisfaction, might influence the relationship between flow and social media addiction.

In summary, the results of this study enrich our understanding of the mediating role of algorithm awareness in the relationship between information exposure and social media addiction. By revealing how awareness of algorithms influences addictive behavior, this study emphasizes the importance of integrating this knowledge into the analysis of problematic digital platform use. Furthermore, we have deepened the understanding of the impact of socially relevant motivations, such as information-seeking and social interaction, and how these affect user behavior through the flow experience. The serial mediation model, which includes both flow and algorithm awareness, offers a novel perspective on the psychological mechanisms underlying addiction, demonstrating that the flow state intensifies engagement with platforms, while algorithm awareness may help mitigate this impact.

Some limitations on this study must be recognized. First, all participants in this study were university students. The mechanisms that work for high school and younger adolescents still need to be further explored. Second, the current research heavily depended on self-reports, which can be affected by recall and desirability bias. Furthermore, this study is cross-sectional and thus unable to obtain the causal directional relationships between the related motivations, flow, algorithm awareness, and addiction. Future research with a longitudinal design is needed to establish the causal direction of the relationships among these variables.

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