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DOES SOCIAL IDENTIFICATION WITH INFLUENCERS IMPACT SOCIAL MEDIA FATIGUE AMONG UNIVERSITY STUDENTS? THE ROLE OF ALGORITHM AWARENESS AND INFORMATION OVERLOAD

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Abstract

Social media has radically transformed our social interactions, becoming one of the most used communication channels. In this context, social identification with influencers has encouraged greater involvement and dependence on social media. However, there is still a lack of understanding regarding how this contributes to social media fatigue and how it relates to algorithm awareness and information overload. This study aimed to explore these relationships among 336 university students (76,8% women) aged 18 to 23, using a serial mediation approach through structural equation modeling. The results highlight the importance of understanding how social identification with influencers affects social media fatigue, as well as the relevance of algorithm awareness and information overload in this process. These findings enrich our understanding of the underlying mechanisms of social media fatigue and emphasize the need to consider cognitive and perceptual aspects in future research and in the design of practical interventions.

KEY WORDS: *Social identification, fatigue, social media, information overload, algorithm*.

Resumen

Las redes sociales han transformado radicalmente nuestras interacciones sociales, convirtiéndose en uno de los canales de comunicación más utilizados. En este contexto, la identificación social con los influencers ha fomentado una mayor implicación y dependencia de las redes sociales. Sin embargo, aún falta comprender cómo contribuye a la fatiga en las redes sociales y cómo se relaciona con el reconocimiento del algoritmo y la sobrecarga de información. Este estudio se propuso explorar estas relaciones en 336 jóvenes universitarios (76,8% mujeres) de 18 a 23 años, utilizando un enfoque de mediación serial a través de ecuaciones estructurales. Los resultados destacan la importancia de entender cómo la identificación social con influencers afecta la fatiga en las redes sociales,

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así como la relevancia del reconocimiento del algoritmo y la sobrecarga de información en este proceso. Estos hallazgos enriquecen nuestra comprensión de los mecanismos subyacentes a la fatiga en las redes sociales y enfatizan la necesidad de considerar aspectos cognitivos y perceptivos en futuras investigaciones y en el diseño de intervenciones prácticas.
PALABRAS CLAVE: *identificación social, fatiga, redes sociales, sobrecarga de información, algoritmo.*

Introduction

We live in an era of booming virtual social media that has experienced dizzying growth over the past two decades. Several platforms, including Facebook, Twitter, Instagram, TikTok, and WhatsApp, have become some of the most downloaded and widespread applications in the world, especially among the younger population (Martínez-Martínez, et al., 2020; Muñoz-Rodríguez, et al., 2020). By offering a range of audiovisual content, like images, short videos, and brief texts, social media has revolutionized the way we of interaction and socialization, keeping us constantly connected to these applications (Bossen et al., 2020; Suárez-Álvarez et al., 2021).

On the other hand, social media implements recommendation algorithms based on user interactions and a series of filters, including methods based on user collaboration, content analysis, demographic characteristics, as well as hybrid approaches (Kardan et al., 2013). These algorithms are designed to analyze user behavior and provide personalized content that matches their interests and preferences. However, the increase in problematic use of these platforms, largely driven by parasocial motivations and the influence of these algorithms, represents a significant challenge for the young population (Martínez-Martínez et al., 2022; Morán-Pallero et al., 2021).

Even though this emerging phenomenon of social media has lately seized the interest of academics and researchers (Iannone et al., 2018; Ramya et al., 2024), empirical studies on the relationship between social identification with influencers and social media fatigue remain scarce. Furthermore, the fundamental processes through which awareness of algorithms and the perception of information overload lead to negative psychological outcomes, such as social media fatigue, particularly in young people, are not well understood.

The need to better understand these dynamics and their implications for the psychological well-being of young users is evident. It is essential to further investigate the factors leading to social media fatigue and develop effective strategies to tackle this growing concern in today's digital era.

The recommendation algorithms, now ubiquitous across platforms, are recognized for providing users with automatic, personalized suggestions by analyzing data such as clicks, views, search queries, ratings, or user comments, and customizing content to align with users' preferences, beliefs, and tastes, as discussed by Rassameeroj and Wu (2019). As users engage with these tailored platforms, they provide additional data, enabling the system to recommend suitable content and personalize the overall experience (Cho et al., 2020).

Researchers in communication and journalism often express concern over the negative aspects of algorithmic mediation (Rodríguez, 2017), such as the reduction of the diversity of information available to users due to the automatic personalization of content (Bajaña, 2021). Thus, the concept of algorithm awareness, which refers to the recognition of algorithms' presence and function in online content, is central to their focus (Swart, 2021). This awareness develops through user experience and has been positively associated with the frequency of use and exposure (Eslami et al., 2015). Meanwhile, Concurrently, the growing utilization of social media, and consequently the generation of extensive social data, can elevate the likelihood of information overload (Kaufhold, 2020; Olshannikova et al., 2017).

Cognitive load theory, developed by John Sweller (1988), focuses on how information is processed by the human mind and how this processing affects learning. According to this theory, the processing capacity of working memory is limited; therefore, learning can be negatively affected if this capacity is exceeded. In this context, perceived information overload occurs when an individual's cognitive capacity for processing information is surpassed by an excessive amount of incoming information (Guo et al., 2020; Pang et al., 2021). According to cognitive load theory, when social media applications with recommendation algorithms send various notifications and update news feeds based on users' habitual review behavior, users regularly review this type of information and often end up receiving more than they desire, exceeding their capacity to process it effectively (Salo et al., 2018). Hence, we put forward the following hypothesis:

H1. Algorithm awareness has a direct and positive effect on the perception of social media information overload.

Social media influencers have been increasingly popular among young adults, with these "micro-celebrities" often regarded as the new opinion leaders and credible sources of information on social media platforms, as argued by Hudders et al. (2021) and Uzunoğlu et al. (2014). According to Lin et al. (2018), when these influencers portray themselves as experts or professionals on these platforms, they manage to establish a distinct social standing within their follower base.

The concept of social identification with influencers has enjoyed notable popularity in research literature. In these parasocial relationships, a regular user is knowledgeable about a celebrity's engagements, such as those of a famous actor, but not vice versa (Baek et al., 2013). Specifically, it involves the relationship that individuals form and sustain with media personalities like celebrities or influencers, where the sense of closeness to these figures is typically one-sided (Hoffner et al., 2022; Lozano-Blasco et al., 2023). It is essential to distinguish between social identification, which involves sharing characteristics or values with the influencer, and emotional bond, which refers to a personal affective connection, such as admiration or affection. Social identification with influencers is driven by an unsatisfied need for belonging and a dependence on media use, both factors encourage consumers to seek alternative sources of interpersonal relationships, especially in the realm of social media (Knoll, 2016). In this sense, the level of this identification may be positively linked to their degree of engagement. It is suggested that as social identification with influencers becomes stronger, it will encourage viewers to use social media more frequently (De Bérail, 2019), which in turn may increase the risk of experiencing fatigue. Therefore, the following hypothesis is formulated:

H2. Social identification has a direct and positive effect on the social media fatigue.

It is worth noting that, although it might seem that a strong identification with influencers could lead to a "blindness" to the impact of algorithms, the reality is different. Social identification not only involves belonging to or affinity with the group represented by the influencer but also critical reflection on the content. This can make users more aware of the algorithms influencing the visibility of the content promoted by influencers (Beer, 2017; Zarouali et al., 2021). Drawing upon these findings, the subsequent hypotheses are formulated:

H3. Social identification has a direct and positive effect on algorithm awareness.

From a clinical standpoint, social media fatigue is described as an emotional state that individuals self-regulate, marked by feelings of tiredness, disillusionment, boredom, and mental exhaustion due to Information overload, as noted by Ravindran et al. (2014) and Teng et al. (2021). Information overload could be exacerbated by the way algorithms present and filter large amounts of content on social platforms, surpassing users' processing capacity. This, in turn, could lead to significant fatigue, as users invest additional cognitive effort in trying to understand and make sense of this content. Thus, a greater understanding of algorithms might intensify these feelings of fatigue by making users more aware of the limitations and manipulative effects of these systems, which could lead to frustration and a sense of lack of control over the content they consume. If this reasoning is accurate, we can expect that:

H4. Algorithm awareness positively influences social media fatigue.

H5. Social identification with influencers indirectly and positively influences social media fatigue through algorithm awareness.

Delving deeper into this topic, companionship is a key motivation for the use of social media in terms of the gratifications that digital media can offer. Regarding how digital media provide gratifications, social media platforms offer opportunities for individuals to sustain parasocial connections and a sense of community with influencers, even without reciprocal relationships, as discussed by Blight et al. (2017) and Bond et al. (2021). Hartmann (2016) notes that these parasocial relationships can serve as substitutes for a lack of real-life connections, fulfilling the need for belonging. As a result, Bond (2021) and Iannone et al. (2018) suggest that individuals experiencing social deficiencies in their offline networks and a strong need to belong may develop a deep social identification with influencers on social media.

While numerous studies have explored the effects of parasocial interaction between influencers and their followers on social media (Boerman et al., 2020), limited research has focused on how it influences the perception of information overload. According to cognitive load theory, social identification with influencers may exacerbate this effect, as users who establish strong identification bonds with influencers on social media may experience even greater pressure to stay informed and active. This increases cognitive load as they try to keep up with the constant flow of content and updates relevant to these influencers. Thus, the subsequent hypotheses are suggested:

H6. Social identification with influencers is positively related to perceived information overload.

H7. Social identification with influencers is positively related to perceived information overload through algorithm awareness.

On the other hand, the effects of information overload on psychological states and how stress from overload could trigger feelings of fatigue, anxiety, and depression, as well as behavioral problems, have been the focus of previous research (Delpechitre et al., 2019; Zhang et al., 2022). In this regard, previous research has adopted the theoretical stress-strain-outcome model to investigate how factors lead to social media fatigue (Lee et al., 2016; Pang, 2021). Stressors referring to environmental stimulants such as technological and media information overload exert an impact on individuals' strain, such as fatigue (Lee et al., 2016). Malik et al. (2021) describe social media fatigue as a mental health concern, noting that its severity differs among individuals. Based on the literature, this study predicts:

H8. Information overload may be positively linked to social media fatigue in young individuals.

H9. Social identification indirectly influences social media fatigue via information overload.

Method

Participants

A stratification procedure was applied to reflect the target population according to age, gender, and education criteria to allow the sample to represent young undergraduate students (*M*= 19.81, *SD*= 1.43). The final study sample consisted of university students (*n*= 336) with 76.8% females and 23.2% males. Additionally, 81.3% of participants reported spending more than three hours per day on social media, and 94.0% admitted to using them for more than three years. The demographic characteristics' descriptive statistical analysis results are presented in Table 1.

Instruments

a) *Social Identification with the Influencer Scale* (SISI; Leach et al., 2008). The scale was assessed using three items and was culturally adapted for the Chinese context. This Likert scale includes five points ranging from 1 (strongly disagree) to 5 (strongly agree) and has been designed to measure identification in various situations, with its reliability confirmed in different contexts (Bartels et al., 2019; Savela et al., 2021). An example item is: "I feel a bond with this influencer." Scores for each item were averaged, where a higher value suggests a stronger parasocial relationship. In the present research, the recorded Cronbach's alpha coefficient was .76, indicating solid internal consistency.

Table 1
The sample's demographic profile (*N*= 336)

Demographic profile	*n*	%
Age		
18-20	228	67.9
21-23	108	32.1
Gender		
Male	78	23.3
Female	258	76.8
Daily hours on social media		
<1	11	3.3
1-2 h	52	15.5
3-4 h	129	38.4
More than 5 h	144	42.9
Duration of social media use		
<1 year	4	1.2
1-2 years	16	4.8
3-4 years	68	20.2
More than 5 years	248	73.8

b) *Algorithmic Media Content Awareness Scale* (AMCA; Zarouali et al., 2021), Chinese version by Wang and Guo (2023). This scale, which assesses the level of awareness of algorithms operating in the selection and presentation of content on social media, has been successfully validated across multiple online platforms. It consists of 13 items covering four dimensions: content filtering, algorithmic decision-making, human-algorithm interaction, and ethical implications (e.g., whether recommended multimedia content on social media depends on the user's online behavior on that platform). Responses were rated on a scale from 1 (not at all aware) to 5 (fully aware). As the mean score increases, the level of algorithm awareness also increases (Cronbach's alpha= .84).
c) *Information Overload Scale* (IOS). The measurement of information overload was adapted from the works of Qaisar et al. (2022) and Cao et al. (2018), the latter having been validated with university students in China. It consists of four items (e.g., "I frequently get distracted due to the excessive amount of information on social media."). Evaluation was conducted on a 5-point Likert scale (1= very rarely, 5= very often). As the average score increases, the level of information overload also increases. In this study, Cronbach's alpha coefficient of .71 was obtained, indicating good internal consistency.
d) *Social Media Fatigue Scale* (SMFS). Social media fatigue was assessed using three statements adapted from a previous study (Malik et al., 2021) and from the study by Zhang et al. (2016), which was validated in a Chinese population.

The items included: “I feel tired when using social media these days”, “I feel emotionally exhausted after using social media these days”, “I get bored when using social media these days”. All questions were rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Mean scores were calculated to indicate the level of social media-related fatigue (Cronbach's α= .83).

Procedure

We shared the questionnaire with 5 researchers and social media users to evaluate content validity and review the appropriateness, readability, and any potential ambiguities in the Chinese version of the scales. Adjustments were made based on their feedback. Additionally, a pilot test with 30 participants was conducted before launching a large-scale survey to verify the scales' reliability and validity.

Subsequently, the questionnaires were collected at two public universities located in Beijing and Langfang, China, through an online survey in January 2024. The study participants were social sciences students at these universities. We focused primarily on inviting university students to take part in the survey, as they represent the largest segment of social media users and are among the most active participants on mobile social platforms (Shao et al., 2019).

Data analysis

The data analysis utilized IBM SPSS Statistics v. 26.0 and SmartPLS 4.0 software. SPSS was used to present descriptive statistics, including the mean and standard deviation. The internal consistency of all scale dimensions was assessed through Cronbach's α coefficient. Following Anderson and Gerbing's (1988) two-step approach to Structural Equation Modeling (SEM), the measurement model was used to confirm the reliability and validity of the constructs, while the structural model tested the hypotheses.

SmartPLS 4.0 was chosen as the primary statistical tool for analyzing both the quality of the measurement and the path model, for three main reasons. Firstly, compared to covariance-based SEM, PLS (Partial Least Squares) can evaluate latent variables with non-normal statistical distribution (Ringle et al., 2012). Secondly, we chose a PLS approach since it is more suitable for examining relatively novel relationships and delving into theories (Gefen et al., 2011). Although theories such as uses and gratifications are used to explain factors leading to information overload and fatigue, the definition and measurement of algorithm awareness have never been studied in the field of these information perception paths before. Therefore, a PLS approach is considered appropriate for our study due to the exploratory nature of the effect of algorithm awareness on social media use. Third, PLS-SEM provides researchers with several parameter values to assess the effectiveness of the conceptual framework in elucidating the observed data, encompassing measures such as goodness of fit, R-squared and predictive relevance (Ramya et al., 2024). The measurement model and the structural model underwent evaluation through a similar two-step procedure. SmartPLS also provides key quality indicators, including factor loadings, composite reliability, Cronbach's alpha, and average variance extracted, to efficiently and accurately assess model reliability and validity.

Results

Measurement model

Table 2 presents the descriptive statistics along with the factor loadings, composite reliability, Cronbach's alpha, and average variance extracted for the model's constructs. Reliability of the scales was assessed using composite reliability and Cronbach's alpha, with satisfactory levels indicated by values between .70 and .95 (Sarstedt et al., 2017). In this study, composite reliability for the constructs ranges from .816 to .900, meeting the required standards. Additionally, all constructs have Cronbach's alpha values above .70, confirming good internal consistency reliability.

Table 2
Psychometric properties of assessment instruments (*N*= 336)

Variables	*M*	*SD*	Range	Skewness	Kurtosis	Loadings	Cronbach's alpha	Composite reliability	AVE
Social identification									
SI1	3.22	1.01	4.00	-.40	-.04	.778	.759	.861	.673
SI2	2.93	0.96	4.00	-.38	-.20	.834			
SI3	2.83	1.05	4.00	-.18	-.51	.848			
Algorithm awareness									
ADM	3.34	0.64	4.00	.24	.70	.706	.843	.895	.683
ETH	3.69	0.65	3.33	.12	-.21	.882			
FIL	3.66	0.66	4.00	-.26	1.16	.801			
HAI	3.65	0.65	3.00	.10	-.21	.903			
Information overload									
IO1	3.41	0.87	4.00	-.25	-.16	.689	.706	.817	.528
IO2	3.15	0.89	4.00	-.12	-.13	.744			
IO3	3.34	0.97	4.00	-.31	-.18	.742			
IO4	3.27	0.97	4.00	-.27	-.04	.729			
Social media fatigue									
F1	3.69	0.80	4.00	-.55	.50	.904	.833	.900	.750
F2	3.71	0.80	4.00	-.68	.85	.897			
F3	3.43	0.91	4.00	-.34	.05	.792			

Note: SI= social identification; ADM= automated decision making; ETH= ethical considerations; FIL= filtering; HAI= human-algorithm interaction; IO= information overload; F= fatigue; AVE= average variance extracted.

Evidence of validity related to internal structure was determined by verifying the factor loadings of the measurement items and the average variance extracted (AVE) for each construct. The factor loadings of the measurement items are above .60, which is considered good to very good, as values between .40 and .70 indicate good correlation, and values above .70 suggest that the factor explains a large portion of the variable. This confirms a strong relationship between the items and their latent constructs. Additionally, the average variance extracted (AVE) for all constructs is above .50, which is adequate according to standards, indicating that the constructs explain, on average, at least 50% of the variance of their indicators. The results indicate strong convergent validity for the constructs (Sarstedt et al., 2017).

The correlations between the variables in Table 3 indicate a positive relationship between social identification and algorithm awareness (0.138), as well as between social identification and information overload (0.212). The direct relationship between social identification and social media fatigue is very weak (.019). On the other hand, a positive correlation is observed between algorithm awareness and information overload (.256), and between algorithm awareness and social media fatigue (.384), suggesting that higher awareness of algorithms is associated with greater information overload and social media fatigue. Finally, there is also a positive correlation between information overload and social media fatigue (.265).

Table 3

Analysis of the correlation between latent variables and the square roots of the average variance extracted (AVE)

Variables	1	2	3	4
1. Social identification	0.821			
2. Algorithm awareness	0.138	0.827		
3. Information overload	0.212	0.256	0.726	
4. Social media fatigue	0.019	0.384	0.265	0.866

Discriminant validity is considered satisfactory when the square root of the average variance extracted (AVE) for each latent variable exceeds the correlations between that variable and others (Bagozzi, 1981). In this study, table 3 displays the AVE square roots on the diagonal, all of which are higher than the correlations with other constructs, indicating strong discriminant validity.

Due to the reliance on self-reported data from a sole source, there exists the potential for common method bias (CMB) among the constructs within the research framework. To assess this, a Harman's single-factor test was conducted. If a single factor accounted for more than 50% of the variance, it would indicate significant common method bias (Harman, 1976). Results revealed that the dominant factor explained only 19.7% of the variance, suggesting that the impact of common method bias in this study is minimal.

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Measurement model

An analysis of PLS-SEM was conducted using SmartPLS 4.0 to examine the path relationships between constructs. The bootstrapping technique was used to gauge the significance levels of the path coefficients. As recommended by Hair et al. (2012), the total number of bootstrap samples was established at 5000.

We assessed the model using the coefficient of determination (R^2), which indicates the variance in a dependent variable accounted for by the independent variables. The R^2 value for social media fatigue was 0.181, surpassing the suggested minimum of 0.100 (Chin, 1998), indicating that the model explains a sufficient amount of variance in the endogenous constructs.

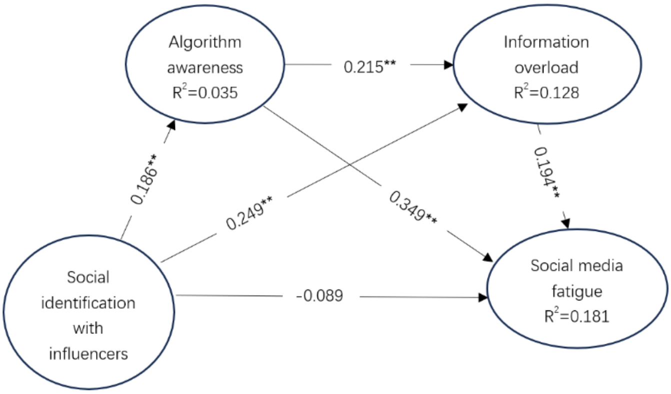
Moreover, an assessment of predictive relevance (Q^2) for the research model was conducted using the blindfolding technique (Shmueli et al., 2019). The findings revealed that the Q^2 values for social media fatigue (0.127), information overload (0.043), and algorithm awareness (0.011) exceeded zero, signifying satisfactory predictive relevance of the model (Hair et al., 2017; Shmueli et al., 2019). In summary, the results of the PLS prediction assessment indicated that the research model demonstrated predictive power.

Figure 1 illustrates the results of the structural model analysis to examine the hypotheses. It can be observed that most of the hypotheses are significant, revealing the essential impact of the relative factors on university students' fatigue. Social identification with influencers shows a direct positive relationship with algorithm awareness (β= 0.19, p< .01) and information overload (β= 0.25, p< .01). However, its relationship with social media fatigue is not supported (β= -0.09, p> .01). Therefore, evidence was found in support of hypotheses H3 and H6, but hypothesis H2 was rejected. Algorithm awareness positively affects information overload (β= 0.22, p<0.01). Meanwhile, algorithm awareness and information overload positively affect social media fatigue, with path coefficients of 0.35 and 0.19 (p< .01), respectively. Thus, evidence was found to support hypotheses H1, H4, and H8.

Bias-corrected 95% confidence interval (CI) bootstrap tests with 5000 resamples were conducted to examine the mediating effects (Table 4). An effect was considered significant if the 95% CI did not include zero. We found that both indirect effects of social identification on overload (effect= .04, 95% CI= [.008, .084]) and on fatigue (effect= .065, 95% CI= [.016, .114]) through algorithm awareness were significant and positive. Therefore, evidence was found in support of hypotheses H5 and H7. Similarly, its indirect effect on fatigue through overload (effect= .048, 95% CI= [.014, .091]) was significant. Consequently, evidence was found in support of hypothesis H9.

Figure 1

PLS results of the structural model



Note: $**p< .01$.

Tabla 4

Mediating effect test

Path	Effect	Lower	Upper
Indirect Path			
Identification → Algorithm → Overload	0.040	0.008	0.084
Identification → Algorithm → Fatigue	0.065	0.016	0.114
Identification → Overload → Fatigue	0.048	0.014	0.091

Discussion

The present research reveals the complex interplay between social identification with influencers, algorithm awareness, information overload, and social media fatigue in university students. The findings indicated that social identification with influencers has a significant impact on algorithm awareness and information overload. Although no significant direct impact of social identification with influencers on social media fatigue was found, an indirect effect through algorithm awareness and information overload was observed. Consistent with the findings of Lin et al. (2020) and Lee et al. (2016), information overload is similarly associated with social media fatigue. Additionally, algorithm awareness also demonstrated a positive association with social media fatigue. This highlights its mediating role in this relationship and the need to consider these factors when analyzing social media fatigue. The absence of a significant direct relationship between social identification with influencers and social media fatigue, as observed in our study, can be explained on several levels. First, although it was initially hypothesized that identification with influencers might encourage more frequent use of social media (De Bérail, 2019), and therefore greater fatigue, the results show that frequent use alone does not necessarily cause fatigue. This may be because users experience positive reinforcement and satisfaction from following these influencers, which counteracts the negative effects of increased use. Additionally, our results indicate that social media fatigue is more directly related to factors such as information overload and algorithm awareness. In this context, social identification with influencers influences these mediating factors: the perception of algorithms, which can intensify feelings of being manipulated and loss of control, and the perception of cognitive overload, which can ultimately trigger significant fatigue. Therefore, the impact of identification with influencers on fatigue is indirect, mediated by these factors.This interpretation is consistent with theories on information saturation and the role of algorithms in the perception of cognitive load (Heiss et al., 2023; Pang, 2021). Thus, our findings highlight the need to consider not only identification with influencers but also how this interaction is mediated by the structure and functioning of digital platforms. These platforms have the capacity to significantly shape the user experience, affecting both the perception of information and the fatigue that users experience.

These findings hold considerable theoretical and practical significance. Theoretically, they contribute to our understanding of the underlying mechanisms of social media fatigue in university students, highlighting the significance of factors like social identification, algorithm awareness, and information overload. This study expands our understanding of social media fatigue by examining not only social media usage behavior but also underlying cognitive and perceptual factors. It underscores the importance of an integrated approach that considers both the direct relationships between variables and the mediating processes that modulate them.

Previous research has indicated that parasocial relationships that individuals develop with media celebrities or imaginary characters could accelerate individuals' socioemotional connections, particularly when they experience social ostracism and thus have a high need for belongingness (Kurtin et al., 2018). In this regard, when individuals identify with certain individuals on social media, they are inclined to pay attention to the information those individuals share and how that information is presented in their feeds. This can lead to greater awareness and understanding of algorithm functioning, as individuals are more motivated to understand how content is selected and displayed based on their connections with influencers.

The relevance of algorithm perception in social media fatigue highlights the complex interplay between technology and user experience in the contemporary digital environment. This subjective understanding of the algorithm not only affects how users interact with content but also shapes their expectations and online experiences (Guo et al., 2020). In this regard, algorithm awareness can influence users' perception of control over their social media experience. Individuals possessing higher cognitive capacities are prone to analyze and contemplate, including how they interact with platform algorithms and how these shape their browsing experience (Ramya et al., 2024). This constant reflection can make them more susceptible to experiencing fatigue and frustration. Although they understand how content is selected and presented, this understanding can intensify the feeling of helplessness as they realize they have limited options to customize or control the flow of information (Bucher, 2017). They know that the algorithm filters and prioritizes content according to parameters they cannot easily modify. This perception of a lack of real control can increase the feeling of being manipulated by an external force, contributing to an overall experience of fatigue related to social media use (Pariser, 2011).

From a practical perspective, the findings of this study carry significant implications for the development of interventions targeted towards reducing social media fatigue in university students. Traditionally, strategies to address this issue have primarily focused on limiting screen time or social media use (Teng et al., 2021). However, the findings suggest that these efforts may be insufficient if the way students perceive and process information on these platforms is not considered.

Instead of simply restricting screen time, efforts could focus on educating students on how to interact more healthily with social media. This could include promoting media literacy and critical awareness of algorithm operations, helping students understand how content is selected and displayed in their feeds. A greater understanding of the algorithm can enable students to make more informed and conscious decisions about their social media use (Castillo-Abdul et al., 2022).

As a result, it is essential that educational strategies in digital literacy not only focus on providing technical knowledge about how algorithms operate but also address the potential emotional and cognitive consequences of this knowledge, specifically fatigue and information overload. This approach aligns with previous literature, which suggests that increased critical awareness can lead to heightened perceptions of manipulation and loss of control (Van Dijck, 2013). To mitigate these effects, it is crucial to foster emotional management skills and resilience, helping users maintain a healthier relationship with digital technologies.

Furthermore, it is vital to develop tools and strategies that help users moderate their interaction with digital platforms. This could include designing applications and features within social media that allow users to customize their experiences more efficiently. Platforms could offer clearer configuration options that help users better understand and control the flow of information they receive (Pariser, 2011). By giving students greater control over their social media experience, these interventions could help reduce the sense of information overload and resulting fatigue.

It is important to take into account some limitations in this study. Firstly, it is important to note that all participants included in this study were young university students. While this provides valuable insight into social media fatigue in this specific demographic group, it is crucial to recognize that the results may not fully generalize to other populations, such as high school adolescents or younger individuals. Therefore, further research is needed to more thoroughly explore the underlying mechanism in different age groups.

Secondly, it is essential to acknowledge that this study was carried out in a specific cultural context and with a particular sample of participants. To confirm the validity and reliability of the results, this study should be replicated in different cultural contexts and diverse settings. The influence of cultural, social, and economic factors on algorithm perception and social media experience may vary among different populations, so it is fundamental to explore these differences to acquire a broader comprehension of the phenomenon.

Finally, since the study is cross-sectional, the data were collected at a single point in time, which limits the ability to determine causal relationships between the variables. To address this limitation, it is beneficial to employ a longitudinal study approach in the future.

In summary, this study offers new perspectives on the factors contributing to social media fatigue among university students, highlighting the importance of considering not only social media usage behavior but also related cognitive and perceptual aspects.

References

Anderson, J. C., & Gerbing, David W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), 411-423. doi: 10.1037/0033-2909.103.3.411

Baek, Y. M., Bae, Y., & Jang, H. (2013). Social and parasocial relationships on social network sites and their differential relationships with users' psychological well-being. *Cyberpsychology, Behavior, and Social Networking, 16*(7), 512-517. doi: 10.1089/cyber.2012.0510

Bajaña Tovar, F. (2021). Filtro burbuja: ¿Cuál es el costo de la personalización digital? [The bubble filter: What is the cost of digital personalization?]. *Revista Chilena de Derecho y Tecnología, 10*(1), 29-52. doi: 10.5354/0719-2584.2021.54042

Bartels, J., Van Vuuren, M., & Ouwerkerk, J. W. (2019). My colleagues are my friends: The role of Facebook contacts in employee identification. *Management Communication Quarterly, 33*(3), 307-328. doi: 10.1177/0893318919837944

Beer, D. (2017). The social power of algorithms. *Information, Communication and Society, 20*(1), 1-13. doi: 10.1080/1369118X.2016.1216147

Blight, M. G., Ruppel, E. K., & Schoenbauer, K. V. (2017). Sense of community on Twitter and Instagram: exploring the roles of motives and parasocial relationships. *Cyberpsychology, Behavior and Social Networking, 20*(5), 314-319. doi: 10.1089/cyber.2016.0505

Boerman, S. C., & Van Reijmersdal, E. A. (2020). Disclosing influencer marketing on YouTube to children: The moderating role of para-social relationship. *Frontiers in Psychology, 10*, 3042, 1-15. doi: 10.3389/fpsyg.2019.03042

Bond, B. J. (2021). Social and parasocial relationships during COVID 19 social distancing. *Journal of Social and Personal Relationships, 38*, 2308-2329. doi: 10.1177/02654075211019129

Bossen, C. B., & Kottasz, R. (2020). Uses and gratifications sought by pre-adolescent and adolescent TikTok consumers. *Young consumers, 21*(4), 1747-3616. doi: 10.1108/YC-07-2020-1186

Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society, 20*(1), 30-44. doi: 10.1080/1369118X.2016.1154086

Cao, X., Masood, A., Luqman, A., & Ali, A. (2018). Excessive use of mobile social networking sites and poor academic performance: Antecedents and consequences from stressor-strain-outcome perspective. *Computers in Human Behavior, 85*,163-174. doi: 10.1016/j.chb.2018.03.023

Castillo-Abdul, B., Blanco-Herrero, D., & Muela-Molina, C. (2022). YouTubers y dietas milagros: Implicaciones para la difusión de contenidos de salud entre 2020 y 2021

[YouTubers and miracle diets: The dissemination of health content between 2020 and 2021]. *Revista Latina de Comunicación Social, 80*, 475-494. doi: 10.4185/RLCS-2022-1743

Chin, W. (1998). The partial least squares approach for structural equation modelling. In G. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Laurence Erlbaum.

De Bérail, P., Guillon, M., & Bungener, C. (2019). The relations between YouTube addiction, social anxiety and parasocial relationships with YouTubers: A moderated-mediation model based on a cognitive-behavioral framework. *Computer in Human Behavior, 99*, 190-204. doi: 10.1016/j.chb.2019.05.007

Delpechitre, D., Black, H. G., & Farrish, J. (2019). The dark side of technology: Examining the impact of technology overload on salespeople. *Journal of Business & Industrial Marketing, 34*(2), 317-337. doi: 10.1108/jbim-03-2017-0057

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015 April 18-23). *I always assumed that i wasn't really that close to [her]: reasoning about invisible algorithms in news feeds* [Paper presentation]. 33rd annual ACM Conference on Human Factors in Computing systems, Seoul, Republic of Korea.

Gefen, D., Rigdon, E. E., & Straub, D. W. (2011). An update and extension to SEM guidelines for admnistrative and social science research. *MIS Quarterly, 35*(2), 3-14.

Guo, Y., Lu, Z., Kuang, H., & Wang, C. (2020). Information avoidance behavior on social network sites: Information irrelevance, overload, and the moderating role of time pressure. *International Journal of Information Management, 52*, 102067. doi: 10.1016/j.ijinfomgt.2020.102067

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of use of partial least squares structural equation modeling in marketing research. *Journal of the Academic Marketing Science, 40*(3), 414-433. doi: 10.1007/s11747-011-0261-6

Hair Jr., J.F., Hult, G.T.M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd Ed.). Sage.

Harman, H. H. (1976). *Modern factor analysis* (3rd Ed.). The University of Chicago Press.

Hartmann, T. (2016). Parasocial interaction, parasocial relationships, and well-being. In L. Reinecke, & M. B. Oliver (Eds.). *The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects* (pp. 131-144). Routledge.

Heiss, R., Nanz, A., & Matthes, J. (2023). Social media information literacy: Conceptualization and associations with information overload, news avoidance and conspiracy mentality. *Computers in Human Behavior, 148*, 107908. doi: 10.1016/j.chb.2023.107908

Hoffner, C. A., & Bond, B. J. (2022). Parasocial relationships, social media, & well-being. *Current Opinion in Psychology, 45*, 101306. doi: 10.1016/j.copsyc.2022.101306

Hudders, L., De Jans, S., & De Veirman, M. (2021). The commercialization of social media stars: A literature review and conceptual framework on the strategic use of social media influencers. *International Journal of Advertising, 40*(3), 327-375. doi: 10.1080/02650487.2020.1836925

Iannone, N. E., McCarty, M. K., Branch, S. E., & Kelly, J. R. (2018). Connecting in the Twitterverse: Using Twitter to satisfy unmet belonging needs. *The Journal of Social Psychology, 158*, 491-495. doi: 10.1080/00224545.2017.1385445

Kardan, A. A., & Ebrahimi, M. (2013). A novel approach to hybrid recommendation systems based on association rules mining for content recommendation in asynchronous discussion groups. *Information Sciences, 219*, 93-110. doi: 10.1016/j.ins.2012.07.011

Kaufhold, M. A., Rupp, N., Reuter, C., & Habdank, M. (2020) Mitigating information overload in social media during conflicts and crises: design and evaluation of a cross-platform alerting system. *Behaviour & Information Technology, 39*(3), 319-342. doi: 10.1080/0144929X.2019.1620334

Knoll, J. (2016). Advertising in social media: A review of empirical evidence. *International Journal of Advertising, 35*(2), 266-300. doi: 10.1080/02650487.2015.1021898

Kurtin, K. S., O'Brien, N., Roy, D., & Dam, L. (2018). The development of parasocial relationships on YouTube. *Journal of Social Media in Society, 7*(1), 233-252.

Leach, C. W., van Zomeren, M., Zebel, S., Vliek, M. L., Pennekamp, S. F., & Doosje, B. (2008). Group-level self-definition and self-investment: A hierarchical (multicomponent) model of in-group identification. *Journal of Personality and Social Psychology, 95*(1), 144-165. doi: 10.1037/0022-3514.95.1.144

Lee, S. B., Lee, S. C., & Suh, Y. H. (2016). Technostress from mobile communication and its impact on quality of life and productivity. *Total Quality Management & Business Excellence, 27*(7-8), 775-790. doi: 10.1080/14783363.2016.1187998

Lin, H. C., Bruning, P. F., & Swarna, H. (2018). Using online opinion leaders to promote the hedonic and utilitarian value of products and services. *Business Horizons, 61*(3), 431-442. doi: 10.1016/j.bushor.2018.01.010

Lin, J., Lin, S., Turel, O., & Xu, F. (2020). The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. *Telematics and Informatics, 49*, 101374. doi: 10.1016/j.tele.2020.101374

Lozano-Blasco, R., Mira-Aladrén, M., & Gil-Lamata, M. (2023). Social media influence on young people and children: Analysis on Instagram, Twitter and YouTube. *Comunicar, 74*, 125-137. doi: 10.3916/C74-2023-10

Malik, A., Dhir, A., Kaur, P., & Johri, A. (2021). Correlates of social media fatigue and academic performance decrement: A large cross-sectional study. *Information Technology & People, 34*(2), 557-580. doi: 10.1108/ITP-06-2019-0289

Martínez-Martínez, F. D., González-García, H., & González-Cabrera, J. (2022). Student's social networks profiles: Psychological needs, self-concept, and intention to be physically active. *Behavioral Psychology/Psicología Conductual, 30*(3), 757-772. doi: 10.51668/bp.8322310s

Morán-Pallero, N., & Felipe-Castaño, E. (2021). Self-concept in social networks and its relation to the affect in adolescents. *Behavioral Psychology/Psicología Conductual, 29*(3), 611-625. doi: 10.51668/bp.8321306s

Muñoz-Rodríguez, J. M., Torrijos Fincias, P., Serrate González, S., & Murciano Hueso, A. (2020). Entornos digitales, conectividad y educación. Percepción y gestión del tiempo en la construcción de la identidad digital de la juventud [Digital environments, connectivity and education: Time perception and management in the construction of young people's digital identity]. *Revista Española de Pedagogía, 78*(277), 457-475. doi: 10.22550/REP78-3-2020-07

Olshannikova, E., Olsson, T., Huhtamäki, J., & Kärkkäinen, H. (2017). Conceptualizing big social data. *Journal of Big Data, 4*(1), 1-19. doi: 10.1186/s40537-017-0063-x

Pang, H. (2021). How compulsive WeChat use and information overload affect social media fatigue and well-being during the COVID-19 pandemic? A stressor-strain-outcome perspective. *Telematics and Informatics, 64*, 101690. doi: 10.1016/j.tele.2021.101690

Pariser, E. (2011). *The filter bubble: What the internet is hiding from you*. Penguin Books.

Ramya, J. B., & Alur, S. (2024). the mediating role of parasocial relationship in customer services chatbots among millennials and Gen Z population. *International Journal of Human-Computer Interaction*, 1-13. doi: 10.1080/10447318.2024.2306438

Qaisar, S., Chu, J., Shah, Z., & Hassan, Z. (2022). Effects of social networking site overloads on discontinuous intentions of users: a moderated mediation analysis. *Behaviour & Information Technology, 41*(16), 3530-3551. doi: 10.1080/0144929X.2021.2002411

Rassameeroj, I., & Wu, S. F. (2019, October 22-25). *Reverse engineering of content delivery algorithms for social media systems*. In A. Mohammad, & Y. Jararweh (Eds.), *2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS)* (pp. 196-203). IEEE.

Ravindran, T., Yeow Kuan, A. C., & Hoe Lian, D. G. (2014). Antecedents and effects of social network fatigue. *Journal of the Association for Information Science and Technology, 65*(11), 2306-2320. doi: 10.1002/asi.23122

Ringle, C. M., Sarstedt, M., & Straub, D. (2012). A critical look at the use of PLS-SEM in MIS Quarterly. *MIS Quarterly (MISQ), 36*(1), 3-14. doi: org/10.2307/41410402

Rodríguez-Cano, C. A. (2017). Los usuarios en su laberinto: Burbujas de filtros, cámaras de ecos y mediación algorítmica en la opinión pública en línea [Users in their labyrinth: filter bubbles, echo cameras and algorithmic mediation in online public opinion]. *Virtualis, 8*(16), 57-76.

Salo, M., Pirkkalainen, H., & Koskelainen, T. (2018). Technostress and social networking services: Explaining users' concentration, sleep, identity, and social relation problems. *Information Systems Journal, 29*(2), 408-435. doi: 10.1111/isj.12213

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 1-40). Springer.

Savela, N., Kaakinen, M., Ellonen, N., & Oksanen, A. (2021). Sharing a work team with robots: The negative effect of robotco-workers on in-group identification with the work team. *Computers in Human Behavior*, 115, 106585. doi: 10.1016/j.chb.2020.106585

Shao, Z., & Pan, Z. (2019). Building Guanxi network in the mobile social platform: A social capital perspective. *International Journal of Information Management, 44*, 109-120. doi: 10.1016/j.ijinfomgt.2018.10.002

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European journal of marketing, 53*(11), 2322-2347. doi: 10.1108/EJM-02-2019-0189

Suárez-Álvarez, R., & García-Jiménez, A. (2021). Centennialsen TikTok: tipología de vídeos. Análisis y comparativa España-Gran Bretaña por género, edad y nacionalidad [Centennials on TikTok: Type of video. Analysis and comparative Spain-Great Britain by gender, age and nationality]. *Revista Latina de Comunicación Social, 79*, 1-22. doi: 10.4185/RLCS-2021-1503

Swart, Joëlle (2021) Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. *Social Media + Society, 7*(2). doi: 10.1177/20563051211008828

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257-285.

Teng, L., Liu, D., & Luo, J. (2021). Explicating user negative behavior toward social media: An exploratory examination based on stressor-strain-outcome model. *Cognition, Technology & Work, 24*, 183-194. doi: 10.1007/s10111-021-00665-0

Van Dijck, J. (2013). *The culture of connectivity: A critical history of social media*. Oxford University Press.

Wang, X., & Guo, Y. (2023). Motivations on TikTok addiction: The moderating role of algorithm awareness on young people. *Profesional de la Información, 32*(4), e320411. doi: 10.3145/epi.2023.jul.11

Zarouali, B., Boerman, S. C., & de Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the Algorithmic Media Content Awareness Scale (AMCA-scale). *Telematics and Informatics, 62*, 101607. doi: 10.1016/j.tele.2021.101607

Zhang, S., Zhao, L., Lu, Y., & Yang, J. (2016). Do you get tired of socializing? An empirical explanation of discontinuous usage behavior in social network services. *Information & Management, 53*(7), 904-914. doi: 10.1016/j.im.2016.03.006

Zhang, X., Ding, X., & Ma, L. (2022). The influences of information overload and social overload on intention to switch in social media. *Behaviour & Information Technology, 41*(2), 228-241. doi: 10.1080/0144929X.2020.1800820

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