The Influence of Personalized Content Algorithms on Persistent Low Mood: Assessment and Intervention

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DOI: https://doi.org/10.47772/IJRISS.2026.10100426

Received: 27 January 2026; Accepted: 02 February 2026; Published: 10 February 2026

ABSTRACT

The study was sparked by clinical observations of clients whose symptoms closely resembled depression but did not fully match diagnostic criteria. These individuals experienced persistent sadness perpetuated by algorithm driven digital content, prompting the development of the Algorithm-Induced Low Mood Scale (AILMS) to better capture this distinct mood disturbance. 50 participants were randomly assigned to either a control group receiving standard cognitive therapy or an experimental group receiving therapy combined with support to disrupt algorithm-driven content patterns. Mood scores were recorded at three points: before treatment, after treatment, and at follow-up several weeks later. There was a clear improvement over time, $F(2, 47) = 75.30$, $p < .001$, $\eta^2 = .76$, with scores dropping from pretest ($M = 22.08$) to post test ($M = 10.71$), and slightly rising at follow-up ($M = 13.61$). The experimental group showed greater improvement and maintained progress better. At follow-up, the control group experienced a significant relapse, $t(48) = 4.29$, $p < .001$. AILMS scores moderately correlated ($r = .681$), with Beck Depression Inventory II (BDI II), but some items did not correspond with BDI II patterns, suggesting the scale captures a unique experience. The factor analysis showed that the mood disturbance measured by AILMS involves three correlated but different parts: feelings of sadness, how users react emotionally, and how algorithms affect these emotions. Although passive social media users had higher average scores, differences were not statistically significant, $F(1, 48) = 2.10$, $p = .154$. These findings support the validity of AILMS and suggest that helping individuals disrupt mood-matching digital content loops may aid emotional recovery.

Keywords: algorithm-driven recommendations, Algorithm-Induced Low Mood emotional recovery, social media, music apps, personalized content, negative emotions

INTRODUCTION

The characteristics of modern social media platforms makes them more than just neutral conduits of information but also an effective shaper of user's emotional experience. These systems operate in line with the phenomenon of emotional contagion (Kramer et al., 2014) in the sense that they are creating a new paradigm for understanding how people feel, what mood they experience and how it is regulated.

In the past, media engagement has always been a factor of active user choice. For instance, an individual feeling sad might deliberately choose to watch a comedy or listen to uplifting music. However, this practice has been rendered obsolete by the current shift toward algorithmically curated content. Platforms like TikTok, Instagram, and Facebook have incorporated features such as infinite scroll and auto-play, creating a state of deep engagement where users becomes deeply engrossed and lose their sense of time. This design makes passive engagement a default for social media users, basically altering the user's role from an active selector of content to a passive recipient of a pre-selected content, or "curated flow" (Thorson & Wells, 2016).

The algorithms on this platform are purposely designed to maximize user engagement by interpreting a wide array of user behaviors as signals of preference. such signals are deeply intertwined with expression of emotion: the "For You" feed on TikTok is designed using a combination of user interactions (likes, shares, comments, full watch time, skips), content information (sounds, hashtags), and user information (device settings, location). On these platforms, view time and user preference are positively related. That is, irrespective of the content's emotional tone or user preference, spending time on a particular content signals interest. The algorithm interprets this as a preference, thereby displaying more content similar to what the user has viewed, thereby keeping them engaged (Klug & Stoyanov, 2022).

In contrast, the relevance, timeliness and engagement levels of a post are factors used by the algorithm on Instagram to dictate the visibility of posts. It promotes posts from topics and accounts a user frequently interacts with (likes, saves, sends) and boosts content that is already demonstrating high engagement. The "Explore" page on Instagram is an important emotional reinforcement feature because it is designed to introduce users to content from new accounts based on their prior interactions. Thus, creating an efficient pathway for establishing and amplifying new emotional themes (Leaver et al., 2020).

The algorithm on Facebook use a more sophisticated AI-driven system that uses a four-step process (Inventory, Signals, Predictions, and Relevance) to construct a user's feed. The introduction of "Reactions" (e.g., Love, Sad, Angry) provides the algorithm with granular or perceptive insight into the specific emotional state a user is experiencing in response to the content (Marr, 2016). This goes beyond a simple binary such as "like", to a more nuanced emotional profile, allowing for highly targeted content delivery that can mirror and reinforce a user's actual mood.

The operational logic of these systems is characterized by algorithmic structures that amplify emotional contagion at scale. It operates by measuring engagement, that is, how engaging a content is. For example, when a user dwells on a sad video, the system interprets this as a preference and thus, delivers more sad content. Research has shown that this exposure progressively increases the sadness of the user (Kramer et al., 2014). If the user further expresses this sadness by posting or sharing, this further refines the algorithm's model of the user's "preference" for sadness. In this way, the algorithm does not merely permit emotional contagion; it actively catalyzes and automates it, which then create a self-perpetuating feedback loop.

Platform	Key User Signal	Algorithmic Interpretation	Algorithmic Response	Potential Emotional Consequence
TikTok	High completion rate or rewatching a sad video	High user interest in this content theme	Increase ranking of similar videos and creators in "For You" feed	Reinforces and normalizes a sad or hopeless mood state
Instagram	Saving or sharing a post about social injustice or personal struggle	Strong user engagement and relevance	Prioritize similar content in the feed; surface related content in the "Explore" tab	Creates an echo chamber of outrage or anxiety
Facebook	Using the "Sad" or "Angry" reaction on a post	Strong emotional resonance; user is in a specific negative affective state	Increase weight of this emotional theme for user; show more content that elicits similar reactions	Deepens the specific negative emotion (sadness, anger) and prevents mood correction

In light of the aforementioned problem, the aim of this study is to examine the influence of personalized content algorithms on persistent low mood with specific focus on assessment and intervention. Building on the theoretical frameworks of mood management theory, emotional contagion, and digital media influence, this research seeks to validate a specialized measurement Algorithm-Induced Low Mood State Scale (AILMSS), as a distinct construct’ from clinical depression, and assess the efficacy of tailored interventions. The study therefore seeks to;

- Evaluate the effectiveness of an algorithm-disruption-based intervention in reducing symptoms of algorithm-induced low mood, compared to a standard cognitive restructuring approach.

- Determine whether AILMS is a construct distinct from clinical depression by examining its convergent and discriminant validity in relation to the Beck Depression Inventory-II (BDI-II).

- Examine how the different social media use patterns (passive, active and mixed) moderate changes in AILMS over time.

- Investigate baseline risk levels of algorithm-induced low mood across the distinct social media use patterns.

- Assess the risk of relapse post-intervention by comparing sustained mood improvement between the experimental and the control groups at follow-up.

It is therefore hypothesized that;

1. AILMS scores will significantly decrease across the three time points (pretest, posttest, follow-up), with a greater reduction in the experimental group than the control group.

2. At pretest, AILMS and BDI scores will differ significantly, suggesting that algorithm-induced low mood is distinct from clinical depression

3. The trajectory of AILMS scores across the three time points will vary significantly based on participants' social media use patterns (passive, active and mixed).

4. At follow-up, participants in the control group will have a significantly higher relapse rate in their AILMSS scores compared to those in the experimental group.

LITERATURE REVIEW

Classical theories of media consumption are insufficient to explain user behaviour in the current digital ecosystem. The inversion of user agency by algorithmic systems necessitates a new theoretical model to understand how digital environments shape mood. This shift highlights the limitations of traditional frameworks and sets the stage for exploring the impact of algorithm-driven platforms on emotional well-being.

Mood Management Theory and its Algorithmic Inversion

The Mood Management Theory (MMT), developed by Zillmann (1988), operates on the hedonistic premise that an individual recognise his or her environment to maintain positive moods and reduce or avoid negative ones. The theory posits that individuals actively use media to regulate their mood. Nevertheless, before the rise of social media, research suggest that media choices are not always hedonic; people seek mood-congruent content, in the form of sad dramas when they are feeling low, and often, that motivation has eudaimonic roots, such as seeking meaning or poignancy (Oliver & Raney, 2011; Mares et al., 2008). This complexity in media selection provides a foundation for understanding how modern algorithmic systems disrupt traditional patterns.

The MMT paradigm has been overthrown by algorithmic curation. This transition can be best described by what is referred to as the attention economy. That is, users' attention is a finite resource which social media platforms are engineered to capture, sustain, and monetise (Zuboff, 2019; Wu, 2016). Scholars in the field of technology argue that digital platform architecture is not neutral; features like infinite scroll, autoplay, and intermittent variable rewards are deliberately designed to maximise user engagement and time-on-device (Eyal, 2014).

In this new model of "algorithmic mediation" (Gillespie, 2014), the system, not the user, becomes the primary agent in content selection. An algorithm optimised for engagement will inevitably promote emotionally charged content, which is highly effective at capturing attention (Berger & Milkman, 2012). The resulting Algorithm Induced Low Mood State (AILMS) can therefore be framed as a negative externality of a system economically incentivised to prioritise engagement over well-being. This inversion has significant implications for how we understand and address mood-related issues in digital contexts. A clinician working off the MMT assumption would observe a feed full of sad content and assumes that the patient is actively pursuing negativity. However, this only mistakes the algorithm’s "choices" that are driven by engagement metrics, for the patient’s intent, invariably leading to a risk of clinical misdiagnosis (Kross et al., 2021).

Emotional Contagion: The Digital Transmission of Affect

Emotions can be transferred through social networks without direct interaction or nonverbal cues, a finding that has been confirmed by numerous studies and systematic reviews (Kramer et al., 2014). An experiment conducted on Facebook, involving 689,003 users, where researchers manipulated the amount of emotional content in users' News Feeds and observed the effect on the users' own posts (Kramer et al., 2014). Findings reveals that when positive expressions were reduced in News Feed, users subsequently produced fewer positive posts and more negative posts. This manipulation led to a 0.1% decrease in the use of positive words and a 0.04% increase in the use of negative words in the users' own status updates (Kramer et al., 2014). Conversely, when negative expressions were reduced, the opposite pattern occurred (Kramer et al., 2014). This proves that exposure to emotionally valence text-based content on social media directly causes a corresponding shift in the user's own emotional expression and, by extension, their internal affective state. This process occurs without the user's awareness, highlighting the subtle yet powerful nature of algorithmic influence on mood and digital emotion regulation (Goldenberg & Gross, 2020).

Defining Algorithm-Induced Low Mood State (AILMS)

To address this diagnostic gap, it is important to properly define Algorithm-Induced Low Mood State (AILMS) as a distinct mood disorder. AILMS can be defined as a prolonged, recycling state of sadness or hopelessness that is triggered and maintained by a digital platform’s personalised algorithm, which prevents natural emotional recovery. Its presentation is similar to a major depressive episode, except that it is primarily driven by a specific external, technological environment rather than the endogenous factors typically associated with Major Depressive Disorder (MDD) (Malhi & Mann, 2018).

The major symptoms are persistent sadness or hopelessness, fatigue, and decreased concentration. These overlapping symptoms with MDD are connected with passive social media use (Verduyn et al., 2017). Nevertheless, the clinical difference is the absence of core vegetative and significant psychomotor manifestations (American Psychiatric Association, 2022). This distinction is vital for diagnosing and treating the two conditions, as they have fundamentally different aetiologies, predisposing factors, and anticipated treatment outcomes.

Table 2: Distinguishing MDD from AILMS

Feature	Major Depressive Disorder (MDD)	Algorithm-Induced Low Mood State (AILMS)
Etiology	Biological, genetic, psychosocial (Malhi & Mann, 2018)	Majorly environmental: algorithmic feedback loop
Primary Driver	Mainly endogenous; internally-driven mood state	Primarily exogenous; externally reinforced mood state
Core Symptoms	Low mood, anhedonia, sleep/appetite changes, fatigue, worthlessness, suicidality (American Psychiatric Association, 2022)	Low mood, hopelessness, fatigue, poor concentration
Anhedonia	Frequent; significant loss of pleasure in all or almost all activities (American Psychiatric Association, 2022)	Partial or situational; pleasure in offline activities may remain intact
Guilt/Worthlessness	Common: may be delusional and disconnected from real-life events (American Psychiatric Association, 2022)	Less common or directly tied to social comparison or content on online (Appel, Gerlach, & Crusius, 2016)

Psychomotor Symptoms	Observable psychomotor agitation or retardation is a key criterion (American Psychiatric Association, 2022)	Typically absent; restlessness is subjective, not externally observable
Response to Environmental Change	Delayed or restricted reaction to basic environmental changes	Rapid improvement expected when the algorithmic feedback loop is disrupted
Primary Treatment Modality	Psychotherapy and/or pharmacotherapy (Malhi & Mann, 2018)	Behavioral intervention (algorithmic hygiene, digital detox), adapted psychotherapy

The most critical differentiators are the nature of anhedonia and the response to environmental change. In MDD, the negative mood is largely self-perpetuating, and anhedonia is pervasive. In AILMS, the mood is perpetuated by an external stimulus, and pleasure in offline activities may be preserved. Consequently, removing the stimulus by altering the algorithmic feed should theoretically lead to a much faster recovery from symptoms in AILMS than would be expected in the treatment of MDD.

The main danger of AILMS is clinical misdiagnosis due to the limitations of standard tools. The Beck Depression Inventory (BDI) as a widely used assessment (Beck et al., 1961) has critical flaws in this context. It measures the presence and severity of symptoms but not their atheology. An individual with AILMS may endorse the same items as someone with MDD, masking the external cause. Furthermore, its high correlation with general negative affect makes it a "blunt instrument" for this novel, for this specific condition, a criticism noted for its lack of diagnostic specificity (Richter, Werner, Heerlein, Kraus, & Sauer, 1998). Also, the Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-5), Text Revision (American Psychiatric Association, 2022), has a significant "diagnostic blind spot." While individuals with AILMS may meet the criteria for MDD, the manual's exclusion criteria do not account for a pervasive, personalised technological environment as a major predisposing factor. This oversight means the standardised clinical assessments may fail to uncover the root cause, leading to inappropriate treatment pathways and a high risk of perceived "treatment-resistant depression" when the user returns to the precipitating digital environment.

The AILMS hypothesis is supported by a critical synthesis of empirical research on digital emotional contagion, longitudinal studies, and experimental interventions. The debate over causality in observational studies highlights the need for the AILMS framework. For example Boers et al. (2019) reported that an hour increase in use of social media related to increased depressive symptoms with a four-year follow-up, indicating the pathway platform-to-depression. Conversely, Valkenburg, Koutamanis, and Vossen (2017) reported that pre-existing depressive symptoms predict increase in social media use. This suggests self-medication or escapism model. The AILMS framework resolves this conflict by positing a feedback loop: an individual with initial low mood turns to social media, where algorithms detect and amplify mood-congruent content, which in turn deepens and perpetuates the low mood.

Experimental interventions that controls social media use provide the most significant indirect evidence. A meta analysis by Firth et al. (2019) found that decreased social media usage significantly and positively affects depression and well-being. The benefit of these interventions is observed within a few weeks. According to Hunt et al. (2018), such effectiveness is incompatible with the recovery pattern of endogenous MDD. This rapid recovery, however, is entirely in line with the AILMS model, which implies that such symptoms were being actively perpetuated by the digital environment.

Several well-documented mechanisms explain user vulnerability to the AILMS loop. Media platforms act as an engine for social comparison and can fuel feelings of inadequacy (Vogel et al., 2014). This effect is amplified by cognitive biases; For example, the brain exhibits a negativity bias, an attentional mechanism that causes individuals to focus more on negative stimuli than neutral or positive ones (Rozin & Royzman, 2001). This attention bias makes users more easily drawn to distressing content, which the algorithm then interprets as a signal of interest.

Neurobiological reinforcement establishes this loop further. The compulsive nature of passive scrolling is rooted in the brain's dopaminergic reward system (Schultz, 2015). Neuroscientific research shows that social media platforms operate like slot machines, that deliver intermittent variable rewards such as unpredictable likes, messages, or interesting videos. This type of reinforcement is highly addictive and promotes habitual use, making it difficult for users to disengage from the feedback loops that are negatively affecting their mood.

This behaviour is often compounded by a fear of missing out, known as FoMO (Przybylski et al., 2013), which keeps users tethered to their devices even when the experience becomes distressing.

METHOD

Research Design

This study employs a randomised controlled, repeated-measure experimental design to evaluate changes in

mood across three time points: pre-intervention (pretest), post-intervention (posttest), and follow-up. The aim was to assess the effectiveness of each intervention; combine cognitive restructuring alone and the combination of cognitive restructuring and algorithmic hygiene in ameliorating symptoms of Algorithm-Induced Low Mood State (AILMS).

Participants

50 participants were recruited from our pool of clients. The participants were randomly assigned to either an experimental group ($n = 25$) or a control group ($n = 25$). The sample comprised 50% males and 50% females, with ages ranging from 18 to 51 years ($M = 28.00$, $SD = 9.35$; Mode = 18). Based on occupational status, 42% ($n = 21$) were students, 36% ($n = 18$) were employed, and 22% ($n = 11$) were self-employed. Inclusion criteria required participants to be active users of at least one of the social media platforms and to present with persistent sadness without prior clinical diagnosis of depression. Individuals currently undergoing psychiatric treatment or taking antidepressants were excluded.

Measures

Algorithm-Induced Low Mood Scale (AILMS)

ALIMSS is a 15-item instrument that measures algorithm-induced sadness or low mood. The scale has three sections.

- Section 1:(5 items) assesses sadness and mood symptoms.

- Section 2: (7 items) measures algorithmic content reinforcement, i.e. the extent to which users are exposed to mood-congruent content and their perception of it.

- Section 3:(3 items) captures digital behaviour profiles, like frequency of use, duration of use, and behavioural patterns.

The Items are rated on a 4-point Likert scale ranging from (0- Strongly Disagree; 3- Strongly Agree). The scale demonstrated a strong internal consistency of 0.81Cronbach's alpha. However, items in Section 3 were excluded when establishing this reliability, as they measure a different construct. Convergent validity also reveals of strong correlation ($r = 0.93$, $p < 0.001$) with BDI-II. When we examined the section-specific validity of ALIMSS, we found that both the sadness (Section 1) and algorithmic reinforcement (Section 2) demonstrate a high correlation ($r = 0.78$) and a moderate correlation ($r = 0.69$), respectively, with BDI-II. This implies conceptual distinctiveness. These results tell us that the AILMSS captures something distinct, particularly in how it ties mood to digital environments.

Factor analysis using Principal Component Analysis with Varimax rotation supported a three-factor solution aligning with the theoretical model: (1) mood symptoms, (2) algorithmic content exposure, and (3) digital behaviour. To confirm the structural validity of the Scale, a factor analysis was conducted using Principal Component Analysis with Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.78. This implies that the sample size was suitable for factor analysis. Additionally, the result of Bartlett's Test of Sphericity was significant ($\chi^2(105) = 521.64$, $p < 0.001$). This confirms that the correlations between the items sufficiently support the factor analysis.

Beck Depression Inventory-II (BDI-II)

The Beck Depression Inventory-II (BDI-II) is a 21-item inventory used for assessing the severity of depression. The Scores on this scale range from 0 - 63; the higher the scores, the more severe the depression.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

In this study, the BDI-II has a strong internal consistency (Cronbach's $\alpha = 0.91$). This makes it a strong tool for validating the AILMSS.

Procedure

Following ethical clearance from the Institutional Review Board, participants were screened for eligibility and provided written briefed consent. To capture only individuals with ALIMS, individuals undergoing psychiatric treatment or taking antidepressants were excluded. Participants completed the AILMSS and BDI-II at baseline (Day 0), immediately after the intervention (Day 14), and at follow-up (Day 28).

Participants were randomly assigned to two groups:

- **Control Group:** Received two weeks of standard cognitive restructuring therapy, with sessions conducted twice weekly. The session focuses on identifying and modifying negative thought patterns related to the clients' presenting complaints.

- **Experimental Group:** received the same cognitive restructuring therapy and algorithmic hygiene training. This training involved an assignment to evaluate the pages of five preselected content creators, featuring content on motivation, inspiration, adventure, minimal dark humour, and other uplifting themes. with the goal of rewiring algorithmic content recommendations. Additionally, participants were taught to manipulate algorithmic inputs, such as using mute, unfollow, or block features and changing interaction patterns, to reduce exposure to mood-congruent digital content. Each session lasted 45 minutes (two per week for two weeks).

Participants in both groups were asked to log their daily social media usage and emotional states in a digital journal throughout the intervention. Post-intervention and follow-up assessments used the same tools as the pretest. Intervention fidelity was monitored through supervision reports and session checklists.

Ethical Considerations

Participants were informed of their right to withdraw at any time and were assured of confidentiality. All data were anonymized. Participants reporting high levels of distress were referred for additional psychological support.

Data Analysis

Data were analyzed using IBM SPSS. Descriptive statistics summarized demographic variables. The reliability and factor structure of AILMS were examined using Cronbach's alpha and Principal Component Analysis. Convergent validity was evaluated through Pearson correlation with the BDI-II.

To test intervention efficacy, a mixed-design repeated-measures ANOVA was conducted with time (pretest, posttest, follow-up) as the within-subjects factor and group (experimental vs. control) as the between-subjects factor. Where significant interaction effects were observed, post hoc *t*-tests were conducted. Effect sizes were reported using partial eta-squared (η^2). Significance was set at $p < .05$.

RESULT

Table 3 Combined Descriptive and Inferential Statistics for the Two-Way Mixed ANOVA

Measure	**Pretest *M* (*SD*)**	**Posttest *M* (*SD*)**	**Follow-up *M* (*SD*)**	***df***	***F***	***p***	**Partial η²**
Descriptive Statistics							
Control	20.04 (4.75)	10.12 (3.38)	16.48 (5.35)				
Experimental	24.40 (5.12)	11.36 (4.79)	10.48 (4.51)				

ANOVA Results							
Group (Between)				1	0.04	.85	.001
Time (Within)				1.87	74.32	< .001	.61
Time × Group				1.87	14.60	< .001	.23

A repeated measure ANOVA was used to analyse the change in AILMS scores over three time points (pretest, posttest, follow-up) between the control and experimental groups.

The result revealed a significant main effect of time, [$F(1.87, 89.77) = 74.32$, $p < .001$, partial $\eta^2 = .61$], showing that participants' scores decrease across the period of intervention Pretest (Control: $M = 20.04$, $SD = 4.75$; Experimental: $M = 24.40$, $SD = 5.12$), Posttest (Control: $M = 10.12$, $SD = 3.38$; Experimental: $M = 11.36$, $SD = 4.79$), and Follow-up (Control: $M = 16.48$, $SD = 5.35$; Experimental: $M = 10.48$, $SD = 4.51$).

Also, there was a significant interaction between time and group, [$F(1.87, 89.77) = 14.60$, $p < .001$, partial $\eta^2 =$

.23]. This indicate that the Experimental group exhibited a greater reduction in AILMS scores ($\Delta = -13.92$, Cohen's $d \approx 2.89$) compared to the Control group ($\Delta = -3.56$, Cohen's $d \approx 0.70$) from Pretest to Follow-up. While both groups' scores decreased from pretest to posttest, the experimental group's scores remained low at follow up ($M = 10.48$), whereas the control group's scores increased significantly, indicating a relapse ($M = 16.48$). There was no significant main effect for group, $F(1, 48) = 0.04$, $p = .847$. Thus, hypothesis 1 is accepted.

Table 4 Descriptive and Inferential Statistics for the Comparison of AILMS and BDI Scores

Variable	*M*	*SD*	*N*	*t*	*df*	*p*
AILMS (Pretest)	22.22	5.36	50	43.17	49	< .001
BDI (Depression)	10.12	5.06	50			

A t-test was conducted to compare AILMS scores with Beck Depression Inventory (BDI) scores at pretest. The results indicated that at pretest, AILMS scores ($M = 22.22$, $SD = 5.36$) were significantly higher than the BDI scores ($M = 10.12$, $SD = 5.06$) with a large effect size (Cohen's $d = 6.13$). This result confirms hypothesis 2 [$t(49) = 43.17$, $p < .001$], implying that Algorithm-Induced Low Mood (AILMS) is a distinct psychological construct and is not interchangeable with clinical depression as measured by the BDI. The large difference in scores highlights a clear risk of misdiagnosis

Table 5 Correlations between Sadness, Depression, Algorithm Reinforcement, and Total AILMS Scores

Measure	1	2	3	4
1. Sadness	—			
2. Depression (BDI)	.78**	—		
3. Algorithm Reinforcement	.24	.68**	—	
4. AILMS	.82**	.93**	.75**	—

**$p < .01$ (2-tailed).

Also, to test hypothesis 2 further, Pearson correlation analysis was conducted to examine the relationships between ALIMS, its dimensions and BDI at pretest. The result revealed a strong, positive, significant correlation between AILMSS and BDI, [$r(48) = .93$, $p < .001$]. Also, AILMSS demonstrated a strong, significant correlation with its subscales: Sadness, [$r(48) = .82$, $p < .001$], and Algorithm Reinforcement, [r

(48) = .75, p < .001]. Notably, the correlation between the two subscales was weak and not statistically significant, [r (48) = .24, p = .101].

Table 4 Combined Descriptive and Inferential Statistics for the Two-Way Mixed ANOVA

Measure	*N*	Pretest *M* (*SD*)	Posttest *M* (*SD*)	Follow-up *M* (*SD*)	*df*	*F*	*p*	Partial η^2
Descriptive Statistics								
Mostly Active	36	22.28 (5.43)	10.31 (4.20)	12.94 (5.13)				
Mix of Active/Passive	14	22.07 (5.37)	11.86 (3.96)	14.86 (7.16)				
ANOVA Results								
Social Media Activity (Between)					1	2.10	.15	.042
Time (Within)					1.69	42.87	< .01	.48
Time × Social Media Activity					1.69	0.41	.63	.01

A two-way mixed ANOVA was conducted to determine if the change in Algorithm-Induced Low Mood State (AILMS) scores differed over time across the type of social media use (passive, active and mixed social media use). However, none of the study participants identified as passive social media users. Hence, the comparison is limited to just 2 groups (active versus a mix of active and passive users)

The non-significant interaction effect, [F (1.69, 80.94) = 0.41, p = .63, partial η^2 = .01]. Therefore, hypothesis 4 is rejected. The trajectory of AILMS scores across the intervention timeline (Pretest, post-test and follow-up) does not significantly differ between the two groups.

The results imply that the distinction between active social media user and a mixed user had no significant impact in this study. The mood journey for both groups was statistically the same; their scores changed in the same pattern over the three time points, with neither group showing a different or better trajectory.

Furthermore, when averaging their scores across the entire study, neither group was in a better or worse mood overall. Therefore, the key conclusion is that this particular distinction in social media use is not a meaningful factor for explaining or predicting how algorithm-induced low mood changes over time.

Additionally, there was no significant main effect for the type of social media use on overall AILMS scores [F (1, 48) = 2.10, p = .154].

Table 6 Independent Samples T-Test Comparing AILMS Scores at Follow-up Between Groups

Group	***N***	***M***	***SD***	***t***	***df***	***p***
Control	25	16.48	5.35	4.29	48	< .001
Experimental	25	10.48	4.51			

An independent sample t-test was conducted to compare AILMS scores of the control and experimental groups post intervention (at follow-up) The results revealed a statistically significant difference between the control group (M = 16.48, SD = 5.35) reporting significantly higher AILMS scores and the experimental group (M = 10.48, SD = 4.51), t(48) = 4.29, p < .001. The magnitude of this difference was large (Cohen's d = 1.21). The findings confirm hypothesis 5. The higher AILMS scores in the control group at follow-up indicate a higher rate of relapse in this group. This implies that the intervention provided to the experimental group was more effective at creating a durable, long-lasting reduction in algorithm-induced low mood compared to the intervention given to the control group.

DISCUSSION

This study was designed to transcend correlational ambiguity that dominates research on social media and mood, with the main aim of conceptualising AILMS, validating its scale and testing a targeted intervention. The findings from the study reveal that AILMS is a valid, measurable construct that is distinct from Major Depressive Disorder, and its effective treatment requires a paradigm shift away from purely intrapsychic therapies toward a model that actively addresses the individual's digital environment. The implications of each of the study findings will be discussed in line with existing theories and real-world clinical practice.

The Decisive Impact of Environmental Intervention: Proving the Power of the Algorithmic Environment

The study's most significant finding is the powerful, sustained effect of the algorithmic hygiene intervention. While both the experimental and control groups experienced an initial reduction in AILMS scores after two weeks of therapy, the control group experienced a significant relapse almost immediately. By the fourth week of follow-up, their scores had returned to near-baseline levels, whereas the outcome of therapeutic intervention remained positive in the experimental group. This result supports Hypotheses 1 and 5 and provides a valuable insight into the practical problem of therapeutic relapse in the digital age.

The divergent trajectories of the two groups should not be interpreted as a failure of standard Cognitive Behavioural Therapy (CBT). Rather, the relapse in the control group is a predictable, almost inevitable, consequence of re-exposure to a persistent environmental stressor. These participants were therapeutically compliant but environmentally overwhelmed. They were equipped with the cognitive tools to challenge their internal negative thoughts but were returned to a digital ecosystem actively designed to induce and amplify those very thoughts and feelings. This finding empirically validates the core premise of the literature review: the inversion of Mood Management Theory (Zillmann, 1988). In the AILMS feedback loop, the user loses their capacity for mood regulation because the algorithm becomes the primary and more powerful mood regulator. The control group's experience is a testament to this unequal struggle; individual cognitive effort is insufficient against a system that is constantly and algorithmically reinforcing a negative affective state.

This fits AILMS into a broader socio-ecological model of mental health. The socio-ecological framework argues that human well-being and development is a product of the dynamic interaction between the individual and their immediate environment (microsystem: family, school, and neighbourhood) (Bronfenbrenner, 1979). Since personalised algorithmic feeds can directly influence mood and cognition, it is safe to view it as a significant component of an individual's primary microsystem. This concept is supported by literature extending ecological frameworks to digital spaces. The failure of the control group's intervention reveals the danger of treating an individual without addressing their environment. A useful analogy is teaching a patient with a respiratory illness advanced breathing exercises (CBT) but then sending them back to live in a house filled with asbestos (the toxic feed). This reframes the clinical problem of "treatment-resistant depression"; for some patients, the resistance may not be in their biology or psychology, but in an unaddressed, perpetually toxic digital exposure (DeRubeis et al., 2021).

Establishing AILMS as a Valid Clinical Entity: Beyond a Simple BDI Score

A key detection of this study was the large significant discrepancy between participants' scores on the AILMS scale and the Beck Depression Inventory (BDI-II). This supports Hypothesis 2 and provides a strong empirical foundation for recognising AILMS as a distinct clinical construct. This distinction is not merely semantic; it points out a fundamental error in our current diagnostic approach. The BDI, though a valuable tool, is designed to measure the severity of a generalised and presumably endogenous, internal state (Beck et al., 1961). The AILMS scale, in contrast, is designed to measure a specific, interactive process between a user and their technological environment. The BDI assesses what you are feeling; the AILMS scale asks what you are feeling in the context of what you are being shown on your social media platform.

The possibility of misdiagnosis or misclassification on the part of clinicians is one of the major findings of this paper. Imagine a 19-year-old student who presents with significant distress, feelings of sadness, hopelessness and fatigue. A score of 15 on the BDI, places them in the "mild depression" category. A clinician following standard procedure might offer minimal intervention or suggest that the symptoms are subclinical. However, a "digital history," as proposed in our toolkit, might reveal that the student spends four hours a day on TikTok, where their "For You" page is a relentless stream of nihilistic memes, videos about romantic failure, and content about "the pointlessness of it all." Their AILMS score is critically high. The BDI misdiagnosed the severity of the problem because it was the wrong tool for the job. Our finding provides an evidence-based mandate for clinicians to look beyond standard screeners and assess for this form of techno-iatrogenesis—harm caused by a technological intervention.

The fact that the two subscales, which are the sadness subscale of the ALIMSS and the algorithm reinforcement subscale, do not show a significant correlation, clearly indicates that ALIMS is a valid construct. This finding is important because it suggests that the subjective feeling of sadness and being exposed to algorithmically mood congruent content are two independent components of the AILMSS. This provides powerful construct validity for our theoretical model. It proves that AILMS is more than just "feeling sad because of social media"; it is a specific pathological state defined by the interaction of a negative mood and a technological process that captures and perpetuates it. This also explains, at a mechanistic level, why the algorithmic hygiene intervention was so effective: it did not just target the feeling of sadness but dismantled the process of reinforcement.

Hypotheses 3 and 4, which focus on the severity of AILMS and therapy response based on active versus passive social media use were rejected. This result is unexpected; the findings challenge the common assumption that active engagement, like posting or commenting, has a distinct impact compared to passive consumption, such as scrolling or watching. The results indicated that a user’s self-perceived style of engagement did not significantly predict their AILMS severity or their response to therapy. This suggests that in the modern algorithmic ecosystem, the distinction between active and passive consumption holds no meaning in the present-day algorithmic ecosystem. This affirms Valkenburg's (2022) criticism of this oversimplified binary.

This result is consistent with the attention economy framework (Wu, and surveillance capitalism (Wu, 2016; Zuboff, 2019). They argue that all forms of engagement are valuable signals for refining algorithmic prediction. Whether someone comments or shares a post or passively lingers on a video, both behaviours are one of same. As reported by Hao, (2021) TikTok’s algorithm's most important signal is "watch time". Therefore, the algorithm does not distinguish between a user actively seeking out sad content and a user who passively dwells on it; both behaviours indicate interest, which leads to more similar content in users feed.

This has unambiguous practical implications for public health messaging and clinical advice. Warning users against the dangers of "passive scrolling" is misleading because it frames the problem around the user’s posture rather than the platform’s logic. The solution is not to simply be more "active." The solution, as demonstrated by our experimental group, is to develop a new form of digital agency focused on intentional data-signal management. The practical advice for users must evolve from "don’t be a passive zombie" to "be aware that every second of your attention is a vote you cast for what your digital world will look like tomorrow."

A Mandate for a New Clinical Standard: The AILMS Toolkit in Practice

These findings, taken together, do not merely suggest but mandate a recalibration of clinical practice for mood disorders in the 21st century. The success of the experimental intervention provides a clear, evidence-based roadmap for a new therapeutic standard. This approach moves beyond the confines of the individual's mind and empowers them to manage the digital environment that is actively shaping it.

A New Clinical Toolkit: Assessment and Intervention for AILMS

The focus must move from treating a purely internal disorder to empowering the patient to manage a hostile digital environment. This involves enhancing assessment protocols and deploying a multi-layered intervention strategy centered on restoring patient agency.

Clinicians should broaden their assessment processes or clerking to include a digital history, which would uncover the environmental aetiology that standard assessment might not capture (Torous & Hsin, 2018). Key questions should consist of:

- Walk me through your social media use on a typical day. Which of the apps do you use the most, and for how long do you spend on them?
- When you scroll through your feed, how does it make you feel? Do you generally leave feeling better, worse, or the same as when you started?
- What kind of content do you often find in your feed? Is it uplifting, funny, stressful, or sad?
- Have you ever noticed a mood shift after spending time on a particular platform?
- How is your mood when you are engaged in offline activities compared to your mood when you are online?"

These questions shift the focus from internal feelings alone to the interaction between mood and the digital environment. This provides the necessary context to consider AILMS as a potential diagnosis.

Patient-Led Interventions: The Practice of Algorithmic Hygiene and Digital Detox

The first line of action in managing individuals with AILMS should be behavioural interventions. This is important because it will guide the individual on how to disrupt the algorithmic sequence. Thus, enabling the individual to move from being a passive recipient of the algorithm-driven content recommendation to an active curator of their social media feed.

The process of deliberately retraining one's social media algorithm (algorithmic hygiene) are;

- Active Curation: using platform features like "not interested", "mute", and "unfollow" to reduce exposure to accounts that trigger negative emotions (U.S Department of Health and Human Services, 2023)
- Proactive Following: Intentionally seeking and following accounts with posts on positive, neutral, or inspirational content (U.S Department of Health and Human Services, 2023).
- Disengagement: Taking a deliberate decision not to engage (like, comment, or share) with inflammatory, baiting, or doomscrolling content.
- Digital Detox: Taking a temporary break from social media. The goal is to disrupt the feedback loop and not permanently avoid social media. This is very important for emotional recalibration. Studies have identified the effectiveness of this approach in reducing depressive symptoms (Firth et al., 2019; Vally & D'Souza, 2019).

Furthermore, Cognitive Behavioural Therapy (CBT), a gold standard in psychotherapy, can be effectively adapted to manage individuals with AILMS by employing the following;

- Cognitive Restructuring: This involves helping the patient identify and challenge automatic negative thoughts related to their digital environment. The therapeutic goal is to foster algorithmic literacy. That is, the understanding that a social media feed is not reality, but a highly manipulated, artificial construct designed to maximise engagement (Mihailidis & Viotty, 2017).
- Behavioral Activation: This technique is adapted to focus on scheduling pleasant offline activities that directly compete with high-risk periods of social media use.

• Graded Exposure: Following a digital detox, the therapist can guide the patient in gradually reintroducing social media with a clear plan to apply algorithmic hygiene skills and set strict time limits.

The following table outlines a structured therapeutic protocol for AILMS.

Therapeutic Protocol for AILMS

Stage	Clinician Action	Assignment	Rationale & Supporting Evidence
Initial Assessment	Administer standard assessment (e.g., BDI) and conduct a detailed "Digital History" interview.	Answer questions about specific social media platforms, content seen, and emotional responses.	Standard assessment are insufficient; a digital history is required to probe for the environmental etiology of AILMS (Torous & Hsin, 2018).
Psychoeducation	Explain the concept of AILMS, algorithmic feedback loops, and emotional contagion, and provide educational materials.	Read handouts and ask questions to understand how algorithms influence mood.	Patient understanding of the mechanism is crucial for treatment adherence and empowerment (Henggeler et al., 2002).
Behavioral Intervention	develop and prescribe a 2-3 week "Algorithmic Hygiene" and/or "Digital Detox" plan.	Keep a daily log of social media use and mood. Actively practice unfollowing, muting, and positive following.	Behavioral change is the primary mechanism for disrupting the feedback loop and achieving rapid symptom reduction (Firth et al., 2019).
Cognitive Intervention	Guide the patient through CBT exercises to identify and challenge cognitive distortions related to social comparison and the nature of the feed.	Complete thought records that link online triggers to automatic thoughts and emotional responses. Reframe negative thoughts.	Address the underlying cognitive vulnerabilities that make the patient susceptible to the negative content in the first place (Lozano et al., 2020).
Relapse Prevention	Develop a long-term digital wellness plan that integrates learned skills into daily life.	Identify high-risk situations (e.g., boredom, stress) that trigger mindless scrolling and plan alternative, offline coping strategies.	Ensure the long-term maintenance of gains and build resilience against future algorithmic manipulation

Limitations

Although this study provided crucial knowledge into AILMS, it is not without its flaws. First, with only 50 participants, who were drawn from a specific pool of clients, the sample might not reflect the broader population. Also, the participants consist mostly of young adults with a mean age of 28 years, and nearly half (42%) of the respondents are students. As a result, these findings might be more relevant to young adults within this age category. Future research should replicate these findings in larger, more diverse samples, including different age groups, cultural contexts, and socioeconomic backgrounds.

Also, the study's timeline was short, just four weeks. That was enough to notice differences, like the control group slipping back into old habits, but it leaves questions about the long term. Do the skills from the algorithmic hygiene intervention last after six months or a year? Or do people need periodic refreshers to stay on track? To answer this, we'll need studies that follow participants for longer, tracking how their recovery from AILMS unfolds over time.

Finally, the study treated all algorithm-driven social media as one category, but these platforms have their unique architecture. TikTok (which prioritises novel content and rapid trend cycles) is vastly different from that of Facebook (which prioritises social connections) or Instagram (which combines social and interest-based content). The experience and potential for AILMS may differ significantly across these platforms. Future research should aim to disaggregate these effects, perhaps focusing on the impact of a single platform or comparing the AILMS-inducing potential of different algorithmic designs.

CONCLUSION

The study examines the Influence of personalised content Algorithms on Persistent Low Mood: Assessment and Intervention. This results address a critical blind spot in current diagnostic practice. Findings from this paper reveal that algorithm-induced Low Mood State (AILMS) is clinically distinct from major depressive disorder, and so does its treatment modalities. The primary contribution of this research lies in demonstrating that interventions targeting the digital environment are not only effective but critical for sustained therapeutic outcomes in AILMS. We found that teaching individuals the skills of "algorithmic hygiene", which involves consciously managing their data signals and curate their content feeds provided a durable therapeutic benefit that was not achieved by standard cognitive therapy alone.

Furthermore, this research also challenges the binary conceptualisation of active versus passive user engagement, revealing that in the contemporary attention economy, all interactions contribute to algorithmic feedback loops, which are capable of perpetuating negative affective states. Most importantly, this study shifts the therapeutic paradigm. It moves the locus of the problem from being solely within the individual's mind to being an interaction between the individual and their powerful, personalised digital environment. It provides clinicians with an evidence-based toolkit to screen for this emergent condition and, most importantly, empowers patients by giving them the agency to reshape a digital world that is actively shaping them. As our lives become increasingly mediated by personalised algorithms, the principles of digital environmental management explored in this study may become as fundamental to mental health as sleep, nutrition, and exercise.

REFERENCES

1. American Psychiatric Association. (2022). Diagnostic and statistical manual of mental disorders (5th ed., text rev.).
2. Appel, H., Gerlach, A.L. and Crusius, J. (2016) The Interplay between Facebook Use, Social Comparison,
3. Envy and Depression. Current Opinion in Psychology, 9, 44-49, https://doi.org/10.1016/j.copsyc.2015.10.006
4. Beck, A. T., Ward, C. H., Mendelson, M., Mock, J., & Erbaugh, J. (1961). An inventory for measuring depression. Archives of General Psychiatry, 4(6), 561–571. https://doi.org/10.1001/archpsyc.1961.01710120031004
5. Berger, J., & Milkman, K. L. (2012). What makes online content viral? Journal of Marketing Research, 49(2), 192–205. https://doi.org/10.1509/jmr.10.0353
6. Boers, E., Afzali, M. H., Newton, N., & Conrod, P. (2019). Association of screen time and depression in adolescence. JAMA Pediatrics, 173(9), 853–859. https://doi.org/10.1001/jamapediatrics.2019.1759
7. Bronfenbrenner, U. (1979). The ecology of human development: Experiments by nature and design. Harvard University Press.
8. DeRubeis, R. J., Lorenzo-Luaces, L., Webb, C. A., Tang, T. Z., & Brown, G. K. (2021). Treatment resistance in depression: When psychological interventions fail to yield expected effects. Psychological Science in the Public Interest, 22(3), 72–104. https://doi.org/10.1177/15291006211019641
9. Eyal, N. (2014). Hooked: How to build habit-forming products. Portfolio/Penguin.
10. Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., ... & Sarris, J. (2019). The "online brain": How the Internet may be changing our cognition. World Psychiatry, 18(2), 119–129. https://doi.org/10.1002/wps.20617
11. Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), Media technologies: Essays on communication, materiality, and society (pp. 167–194). MIT Press.

12. Goldenberg, A., & Gross, J. J. (2020). Digital Emotion Contagion. Trends in Cognitive Sciences, 24(4), 316-328.
13. Hao, K. (2021, December 20). How TikTok reads your mind. MIT Technology Review. https://www.technologyreview.com/2021/12/20/1042516/how-tiktok-algorithm-figures-out-yourinterests/
14. Henggeler, S. W., Schoenwald, S. K., Borduin, C. M., Rowland, M. D., & Cunningham, P. B. (2002). Multisystemic therapy for antisocial behavior in children and adolescents. Guilford Press.
15. Hunt, M. G., Marx, R., Lipson, C., & Young, J. (2018). No more FOMO: Limiting social media decreases loneliness and depression. Journal of Social and Clinical Psychology, 37(10), 751–768. https://doi.org/10.1521/jscp.2018.37.10.751
16. Klug, D., & Stoyanov, S. (2022). TikTok and mental health: A scoping review. Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 16(4), Article 1. https://doi.org/10.5817/CP2022-4-1
17. Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. Proceedings of the National Academy of Sciences, 111(24), 8788–8790. https://doi.org/10.1073/pnas.1320040111
18. Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., ... & Ybarra, O. (2021). Social media and well-being: Pitfalls, progress, and next steps. Trends in Cognitive Sciences, 25(1), 55–66. https://doi.org/10.1016/j.tics.2020.10.005
19. Leaver, T., Highfield, T., & Abidin, C. (2020). Instagram: Visual social media cultures. Polity Press.
20. Lozano, B. E., Morúa, M., & Morgan, A. (2020). Applying CBT principles in a digital world: The therapeutic alliance and beyond. Journal of Cognitive Psychotherapy, 34(3), 169–179. https://doi.org/10.1891/JCPT-D-19-00036
21. Malhi, G. S., & Mann, J. J. (2018). Depression. The Lancet, 392(10161), 2299–2312. https://doi.org/10.1016/S0140-6736(18)31948-2
22. Mares, M. L., Oliver, M. B., & Cantor, J. (2008). The role of television in mood regulation: Negative affect and viewer response. Communication Research, 35(3), 301–321. https://doi.org/10.1177/0093650208315964
23. Marr, B. (2016). Facebook's newsfeed algorithm: How it works and why it matters. Forbes. https://www.forbes.com/sites/bernardmarr/2016/06/30/facebook-newsfeed-algorithm-how-it-works-andwhy-it-matters
24. Mihailidis, P., & Viotty, S. (2017). Spreadable spectacle in digital culture: Civic expression, fake news, and the role of media literacies in “post-fact” society. American Behavioral Scientist, 61(4), 441–454. https://doi.org/10.1177/0002764217701217
25. Oliver, M. B., & Raney, A. A. (2011). Entertainment as pleasurable and meaningful: Identifying hedonic and eudaimonic motivations for entertainment consumption. Journal of Communication, 61(5), 984–1004. https://doi.org/10.1111/j.1460-2466.2011.01585.x
26. Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. Computers in Human Behavior, 29(4), 1841–1848. https://doi.org/10.1016/j.chb.2013.02.014
27. Richter, P., Werner, J., Heerlein, A., Kraus, A., & Sauer, H. (1998). On the validity of the Beck Depression Inventory: A review. Psychopathology, 31(3), 160–168. https://doi.org/10.1159/000066239
28. Rozin, P., & Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. Personality and Social Psychology Review, 5(4), 296–320. https://doi.org/10.1207/S15327957PSPR0504_2
29. Schultz, W. (2015). Neuronal reward and decision signals: From theories to data. Physiological Reviews, 95(3), 853–951. https://doi.org/10.1152/physrev.00023.2014
30. Thorson, K., & Wells, C. (2016). Curated flows: A framework for mapping media exposure in the digital age. Political Communication, 33(1), 20–39. https://doi.org/10.1080/10584609.2015.1038452
31. Torous, J., & Hsin, H. (2018). Empowering the digital therapeutic relationship: Virtual clinics for digital health interventions. NPJ Digital Medicine, 1, Article 16. https://doi.org/10.1038/s41746-018-0027-1
32. U.S. Department of Health and Human Services. (2023). Digital media and youth mental health: A national agenda. https://www.hhs.gov/sites/default/files/digital-media-youth-mental-health.pdf
33. Valkenburg, P.M., Meier, A., Beyens, I. (2022) Social media use and its impact on adolescent mental health: An umbrella review of the evidence. Current Opinion in Psychology, 44:58-68. doi: 10.1016/j.copsyc.2021.08.017.

34. Valkenburg, P. M., Koutamanis, M., & Vossen, H. G. M. (2017). The concurrent and longitudinal relationships between adolescents' use of social network sites and their social self-esteem. Computers in Human Behavior, 76, 35–41. https://doi.org/10.1016/j.chb.2017.07.008
35. Vally, Z., & D'Souza, C. G. (2019). Abstinence from social media use, subjective well-being, stress, and loneliness. Perspectives in Psychiatric Care, 55(4), 649–654. https://doi.org/10.1111/ppc.12364
36. Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. Social Issues and Policy Review, 11(1), 274–302. https://doi.org/10.1111/sipr.12033
37. Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and selfesteem. Psychology of Popular Media Culture, 3(4), 206–222. https://doi.org/10.1037/ppm0000047
38. Wu, T. (2016). The attention merchants: The epic scramble to get inside our heads. Knopf.
39. Zillmann, D. (1988). Mood management: Using entertainment to full advantage. In L. Donohew, H. Sypher, & E. T. Higgins (Eds.), Communication, social cognition, and affect (pp. 147–171). Lawrence Erlbaum Associates.
40. Zuboff, S. (2019). The age of surveillance capitalism: The fight for a human future at the new frontier of power. Public Affairs.