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Algorithmic Exposure and Adolescent Mental Health Trajectories: A Longitudinal, Multi-Country Investigation

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ABSTRACT

The pervasive integration of AI-driven algorithmic systems into social media platforms has fundamentally altered the digital landscape for adolescents. This review synthesizes longitudinal and multi-country research on the relationship between algorithmic exposure, characterized by personalization, recommendation intensity, and amplification dynamics, and adolescent mental health trajectories. Findings indicate that algorithmically curated content significantly influences psychological well-being through mechanisms such as social comparison, fear of missing out, and sleep disruption. However, these effects are not uniform; they are moderated by cultural context, digital literacy, and socioeconomic factors. Current research remains limited by methodological fragmentation, overreliance on screen-time metrics, and a geographical bias toward high-income countries. This paper proposes a conceptual framework integrating algorithmic inputs, usage patterns, psychological mediators, and contextual moderators to guide future research. The conclusions emphasize the urgent need for longitudinal, interdisciplinary studies across diverse cultural contexts, greater transparency from technology platforms, and policy-relevant investigations to effectively mitigate risks and promote resilience. A global, evidence-based approach is essential to safeguard adolescent mental health in an increasingly algorithmic digital environment.

Keywords: algorithmic exposure, adolescent mental health, social media, longitudinal studies, cross-cultural research, digital literacy, psychological mediators

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INTRODUCTION

In recent years, social media platforms have become nearly ubiquitous in the lives of adolescents. Platforms such as Instagram, TikTok, YouTube, and Twitter employ increasingly sophisticated AI-driven algorithms to personalize the user experience, tailoring content, advertisements, and recommendations to individual preferences, past behavior, and engagement statistics. These algorithmic systems are designed to maximize engagement by learning what content retains attention, encourages interaction, and keeps users on the platform. While this personalization offers benefits, such as content relevance, community building, and entertainment, there is growing concern about unintended psychological effects, particularly among adolescents.

Adolescence is a developmental period characterized by rapid biological, psychological, and social transformation. It is a time when identity formation, peer influence, emotion regulation, and vulnerability to mental health disorders (such as depression, anxiety, and low self-esteem) are especially salient (Johannes et al., 2021; Vannucci et al., 2020). Because adolescents are still developing cognitive control, coping strategies, and social comparison frameworks, they may be more susceptible to the effects of recommendation algorithms, personalized feeds, "echo chambers," and amplified exposure to emotionally charged content. These AI-driven features can intensify exposure to social comparison, fear of missing out (FoMO), negative body image ideals, cyberbullying, or sensationalist content, thereby potentially accelerating or exacerbating mental health difficulties.

Empirical research has long studied screen time, the total hours spent in front of screens, as a correlate of well-being among adolescents. Systematic reviews and meta-analyses have generally found small to moderate associations between high amounts of screen time and increased risk of depressive symptoms, anxiety, and poorer well-being (Maras et al., 2015; Coyne et al., 2023). For example, a recent meta-analysis of prospective cohort studies reported that adolescents who had higher baseline screen time were at greater risk of developing depression later, though effect sizes tended to be modest. Similarly, large longitudinal studies such as the ABCD (Adolescent Brain Cognitive Development) Study in the United States have found that baseline screen time is prospectively associated with small increases in behavioural and emotional symptoms over follow-ups of one to two years, after accounting for demographic covariates.

However, much of the research to date has conceptualised digital exposure in terms of quantity, total screen time, number of hours on social media, etc., rather than the *quality*, *type*, or *source* of exposure, particularly features driven by AI. Features such as algorithmically-recommended content, personalized feeds, engagement loops, self-presentation pressures, upward social comparison, and interactive versus passive use are less well captured in large-scale quantitative studies. A recent study from Norway using the "LifeOnSoMe" cohort design found that adolescents who placed a high emphasis on self-presentation on social media (e.g., curating one's profile, feedback-seeking, making upward comparisons) had greater levels of depression and anxiety over time, compared to peers with lower such emphasis. This implies that it is not merely *how much* adolescents are using social media, but *how* social media usage (especially features enabled by algorithms) shapes their experiences and exposure.

Moreover, cross-national and cross-cultural evidence is still somewhat limited. Most longitudinal studies are concentrated in high-income countries (HICs), where platform structures, regulatory regimes, digital literacy, and social norms may differ substantially from low- and middle-income countries (LMICs). In LMIC contexts, adolescents often face greater disparities in access, differing levels of digital literacy, diverse cultural norms regarding self-presentation and community, and varying policy environments for content moderation. For example, an Indian cohort study tracking adolescents in Bihar and Uttar Pradesh found that increased social media use over time was associated with increasing depressive symptoms among both boys and girls, illustrating that the patterns observed in HICs may also be present in LMIC contexts, but possibly mediated by different social and environmental factors.

Despite mounting evidence, there remains a substantial gap when it comes to isolating algorithmic personalization as a unique determinant of adolescent mental health. Screen time and social media usage are heterogeneous constructs; they include passive scrolling, consuming algorithmic recommendations, peer interactions, content creation, active feedback loops, and content moderation. These dimensions are often conflated in studies or not adequately distinguished. Longitudinal designs are fewer still, especially those that can account for changes in algorithmic exposure over time, differential uptake of features (e.g., "For You" pages, recommended videos), or changes in platform algorithms themselves. Without finer-grained measurement of algorithmic input and cross-cultural comparisons of exposure and impact, our understanding of causal mechanisms remains limited.

Given these gaps, a review focused specifically on *algorithmic exposure*, how algorithms shape what adolescents see, how they interact, and how that relates to mental health trajectories, is timely and important. Such a review must draw on longitudinal and cross-national evidence to understand not only whether algorithmic exposure is associated with mental health outcomes, but how those associations evolve, what mediators (e.g., social comparison, sleep disruption, self-presentation) and moderators (e.g., culture, socioeconomic status, regulatory environment) are active, and what policy or design interventions might be effective.

*Aim of the Review***.** This review consolidates global evidence on adolescent mental health trajectories in relation to algorithmic exposure on social media platforms. It emphasizes findings from longitudinal and multi-country studies, synthesising what is known about the magnitude of associations, mediating psychological and behavioral pathways, and contextual moderators, with a view toward informing both research and policy.

2. Conceptual Background

2.1- Algorithmic Exposure

“Algorithmic exposure” refers to adolescents’ engagement with content that is curated, personalized, or recommended by AI systems on social media platforms, feeds that dynamically adapt to user behavior, interests, engagement, and network interactions. These algorithmic systems shape what content is surfaced (e.g., posts, videos, ads), how often, and in what order, often optimizing for metrics like retention, clicks, or engagement. Unlike human-curated content, algorithmic exposure can produce feedback loops: what the algorithm learns to show more often becomes more engaging simply because exposure breeds interaction, which in turn reinforces future exposure.

In recent literature, algorithmic exposure has been linked to several domains of risk for adolescent mental health. For example, exposure to extreme or appearance-focused content via recommendation systems has been shown to exacerbate body dissatisfaction, eating disorders, and self-esteem issues (Costello et al., 2024). Algorithms may also amplify sensational or emotionally charged content, giving disproportionate visibility to content that provokes strong reactions, fear, outrage, comparison, because these tend to increase engagement (Costello et al., 2024). The distinction between passive algorithmic consumption (just scrolling or being recommended content) and active participation (posting, interacting) may matter: passive exposure is more strongly associated with upward social comparison and internalizing symptoms (Boers, Afzali, Newton, et al., 2019).

Thus, algorithmic exposure is more than just “time spent on social media”; it includes *which* content is seen (including hidden recommendation pathways), *how* content is presented (e.g., autoplay, endless scroll), and *how* users respond (interaction, avoidance, comparison). In longitudinal designs, it is this nuanced exposure, recommendation intensity, exposure to peer norms or unrealistic ideals, that may carry greater predictive weight for mental health trajectories than gross screen time alone.

2.2- Mental Health Trajectories

Adolescent mental health is dynamic, marked by fluctuating emotional stability, identity, peer relations, and coping. Understanding algorithmic effects requires examining how mental health trajectories evolve—onset, escalation, remission, or resilience—and how coping and environment modulate these paths.

Longitudinal studies illustrate these dynamics:

- **Boers et al. (2019)** found that increased social media and TV use over four years correlated with rising depressive symptoms, supporting upward social comparison and reinforcing spirals.
- **Ravens-Sieberer et al. (2024)** identified distinct symptom trajectories during COVID-19, showing deterioration in some adolescents and stability in others based on stressors and resources.

Positive trajectories like resilience, well-being, and adaptive coping also shift over time. For example, "shift-persist" coping buffers stress, linking physical activity to fewer psychosomatic symptoms (Chen, Done et al., 2021). Coping itself develops: among Chinese children, active vs. avoidant coping predicted different anxiety trajectories over six months (Xiao et al., 2022). Thus, coping serves as both mediator and outcome in adolescent mental health.

2.3- Global Perspective: Cultural Norms, Regulatory Frameworks, and Digital Literacy

Algorithmic exposure on social media is universal, but its psychological effects are moderated by cultural, regulatory, and literacy-based contexts.

Cultural norms shape both content and interpretation. A cross-cultural study (Keles-Gordesli et al., 2025) found that links between social media use and depression vary by individualism–collectivism; in collectivist cultures, peer expectations and stigma influence how algorithmic content (e.g., appearance norms) is internalized.

Regulatory frameworks differ significantly—from strict content moderation and transparency requirements to minimal oversight—affecting what content is promoted and how harm is mitigated (Costello et al., 2024).

Digital literacy critically moderates impact: adolescents with higher literacy recognize bias, manage privacy, and resist social comparison, while those with lower literacy—especially in the Global South—face greater vulnerability despite high exposure (Sher Baz Khan, 2025).

In sum, the conceptual framework for studying algorithmic exposure and mental health trajectories among adolescents must integrate:

1. **Algorithmic input and exposure features** (type, intensity, recommendation mechanisms);
2. **Usage and behavior** (active vs passive, time, patterns of engagement);
3. **Temporal dynamics** of mental health outcomes (onset, worsening or improvement, coping trajectories);
4. **Mediators** (social comparison, FoMO, sleep disruption, emotional regulation);
5. **Moderators** (culture, regulation, digital literacy, socioeconomic status).

S. No.	Study (citation)	Country/setting (sample)	Longitudinal design (waves/	How *algorithmic exposure* was measured/	Key finding

			duration)	**operationalized**	
1	Taylor, S. H., & Chen, Y. A. (2024). *The lonely algorithm problem: the relationship between algorithmic personalization and social connectedness on TikTok.* J. Comput. Mediat. Commun.	US / Global online sample (adolescents & young adults in survey & diary studies)	Two preregistered studies: cross-sectional survey + 2-week daily diary (within-person longitudinal)	**Perceived Algorithm Responsiveness (PAR)** and Perceived Algorithm Insensitivity (PAI), self-reports about TikTok “For You” personalization; daily diary of algorithmic experiences.	Frequent identity-relevant, positively valenced recommendations ↑ PAR were associated with greater momentary social connectedness — highlights human perception of algorithm effects.
2	Salerno, L., Fortunato, L., Lo Coco, G., et al. (2025). *Social support and social comparison tendencies predict trajectories of adolescents' problematic social media use.* PLOS ONE.	Italy, adolescents (N ≈ 403; 13–18 yrs)	Four-wave panel (short intervals across 2024–25)	Objective self-reported device tracking of **time spent on Instagram & TikTok** + measures of problematic/social-addictive use (BSMAS), platform-specific usage as proxy for algorithmic exposure.	Identified trajectory classes where high time on TikTok (algorithmic feed) co-occurred with persistent problematic use; social comparison predicted vulnerable trajectories.
3	UCL / Univ. of Kent algorithm audit & report (2024). *Algorithmic amplification of misogynistic content (TikTok audit).* (Report & audits)	UK (audit via sock-puppet accounts)	Shortitudinal audit (multi-day monitoring; repeated measures across days)	**Sock-puppet / audit method**: created archetypal accounts and tracked how recommendation algorithms amplified misogynistic content over days (For You feed).	TikTok recommender rapidly amplified misogynistic content — proportion of hateful/misogynistic recommendations rose markedly within days. Demonstrates amplification dynamics of recommender systems.
4	Liu, Q., & Li, J. (2024). *A one-year longitudinal study on the mediating role of problematic TikTok use.* Humanities & Social Sciences Communications.	China. university students (N ≈ 590; 17–24 yrs)	3 waves across 1 year (T1, T2 at 6 months, T3 at 12 months)	**Problematic TikTok use** measured (severity & time); problematic use used as a behavioural mediator reflecting intense algorithmic exposure/engagement (proxy).	Problematic TikTok use mediated longitudinal links between academic stress and later outcomes (e.g., procrastination); it highlights the temporal role of heavy/reinforced engagement with algorithmic feeds.
5	Boers, E., Afzali, M. H., Newton, N., & Conrod, P. (2019). *Association of screen time and depression in adolescence.* JAMA Pediatr.	Canada (Greater Montreal), adolescents (N ≈ 3,800; ~12.7 yrs mean)	Annual repeated measures across 4 years	**Screen time subtypes** (social media, TV, computer), used as broad proxies (do not measure algorithmic signals directly).	Within-person increases in social media use predicted increases in depressive symptoms; authors interpret via social comparison / reinforcing spiral mechanisms (relevant to algorithmic personalization).
6	*Lonely algorithms: longitudinal investigation into bidirectional relationships between perceived algorithm*	Mixed samples (studies include Instagram; adolescents & adults)	Longitudinal survey(s) (panel design)	**Perceived Algorithm Responsiveness (PAR/PAI)** measured via self-report across timepoints — perception of	Evidence of bidirectional links: perceived algorithm responsiveness relates to loneliness over time — shows perception of algorithmic curation is

	responsiveness and loneliness (Taylor et al./SAGE 2023).			algorithmic personalization.	longitudinally associated with social outcomes.
8	Zmavc et al. / Longitudinal Problematic Social Media Use in Students (2024–25)	University/student samples (various countries)	Multi-wave longitudinal (6–12 months or repeated visits)	Problematic social media use scales + change over time; some studies include objective device logs (time on apps like TikTok, Instagram), platforms with strong recommender engines.	Increases in problematic social media use over time were associated with increases in depressive symptoms and loneliness, underscoring how reinforced engagement (via algorithms) co-evolves with mental health.
9	Baumann, F., Arora, N., Rahwan, I., & Czaplicka, A. (2025). *Dynamics of Algorithmic Content Amplification on TikTok*. arXiv (sock-puppet longitudinal audit).	Experimental audit (bots / sock-puppet accounts), global simulated environments	Time-series / repeated-exposure audit (watching ~200 videos; measuring feed changes over time)	**Audit with bots** to quantify how quickly and strongly TikTok amplifies interest-aligned content (algorithmic amplification metric).	Fast and strong amplification was observed within the first hundreds of videos watched; amplification reduces content diversity, shows a mechanistic dynamic that could drive longitudinal exposure patterns in human users.

3- Review of Literature

3.1. Algorithmic Design and the Attention Economy

Social media platforms operate within an attention economy, where AI-driven algorithms are engineered to maximize user engagement by learning and reinforcing individual preferences (Baumann et al., 2025). This creates a feedback loop: content that garners interaction is amplified, often leading to the formation of "echo chambers" and "filter bubbles" that limit exposure to diverse viewpoints and encourage addictive, endless scrolling patterns (Boers et al., 2019). The longitudinal design of studies like the Adolescent Brain Cognitive Development (ABCD) Study in the U.S. has been pivotal, linking increases in overall screen time, a common proxy for algorithmic exposure, to small but significant increases in behavioral and emotional symptoms over time. Crucially, this relationship is often mediated by algorithmic features that disrupt sleep patterns, a known predictor of poor mental health in adolescents (Boers et al., 2019).

3.2. Social Comparison and Body Image

Algorithmic exposure intensifies risks associated with social comparison, particularly on highly visual platforms like Instagram and TikTok. These platforms' recommender systems amplify appearance-focused and idealised content, heightening body dissatisfaction and risks for eating disorders, especially among adolescent girls (Costello et al., 2024; Yang et al., 2024). A key finding from longitudinal research is the distinction between active and passive use; passive consumption of algorithmically recommended content is more strongly associated with upward social comparison and internalizing symptoms like depression (Boers, Afzali, Newton, et al., 2019). Cross-cultural differences are evident. While Western studies often emphasize body image and appearance (Salerno et al., 2025), research in Asian contexts, such as China, frequently highlights how algorithmic feeds mediate the relationship between academic stress and negative outcomes like procrastination, pointing to a different focus of social comparison (Liu & Li, 2024).

3.3. Emotional Regulation and Anxiety

The algorithmic prioritization of emotionally charged or sensational content, because it provokes strong reactions and higher engagement, can foster maladaptive emotional regulation, including rumination and anxiety (Costello et al., 2024). Experimental audits using sock-puppet accounts have demonstrated that platforms like TikTok can rapidly amplify misogynistic and hateful content within days, exposing adolescents to harmful normative environments (UCL, 2024). This repetitive exposure to negative affective content can elevate stress responses and contribute to the development of anxiety trajectories. Within-person longitudinal studies have shown that short-term increases in appearance-related consciousness, fueled by algorithmic recommendations, predict concomitant rises in depressive symptoms, underscoring the dynamic and reinforcing nature of this relationship (Yang et al., 2024).

3.4. Cross-National Findings

The evidence base is heavily skewed toward high-income countries (HICs), where longitudinal studies have extensively documented associations between screen time, cyberbullying, and self-esteem issues (Boers et al., 2019). However, emerging research from low- and middle-income countries (LMICs) suggests similar patterns may exist but are mediated by distinct factors. For instance, a study in India found that rising social media use was associated with increasing depressive symptoms, highlighting a global concern (Gupta, S., et. al., 2024). The impact in LMICs may be exacerbated by lower levels of digital literacy, less robust regulatory environments, and different cultural norms around self-presentation and mental health (Keles-Gordesli et al., 2025; Sher Baz Khan, 2025). The following table synthesizes key longitudinal and cross-sectional findings from a diverse set of countries.

Table: 2 Cross-National Studies on Social Media Use, Algorithmic Exposure, and Adolescent Mental

Country	Citation	Study Design & Method	Key Finding
Canada (HIC)	Boers et al. (2019)	Longitudinal (4 years); N ≈ 3,800 adolescents; annual surveys measuring screen time subtypes.	Increased social media use predicts later depressive symptoms.
United States (HIC)	Taylor & Chen (2024)	Mixed-methods: Cross-sectional survey & 2-week daily diary study; measured perceived algorithm responsiveness (PAR) on TikTok.	Perception of a responsive algorithm (high PAR) was linked to greater feelings of social connectedness.
Italy (HIC)	Salerno et al. (2025)	Four-wave longitudinal panel; N ≈ 403 adolescents; tracked time on Instagram/TikTok and problematic use.	High, persistent use of algorithmic feeds co-occurred with problematic use, predicted by social comparison.
United Kingdom (HIC)	UCL (2024)	Experimental audit study; used sock-puppet accounts to track TikTok's recommendation algorithm over days.	The algorithm rapidly amplified misogynistic content to teen-like accounts.
China (UMIC)	Liu & Li (2024)	Longitudinal (3 waves over 1 year): N ≈ 590 university students; measured problematic TikTok use.	Problematic TikTok use mediated the link between academic stress and negative outcomes like procrastination.
India (LMIC)	*Referenced in review*	Longitudinal cohort; tracked social media use and depressive symptoms.	Increased social media use was associated with rising depressive symptoms.
Multi-Country	Keles-Gordesli et al. (2025)	Cross-cultural comparison: adolescents from Türkiye, England, and Ireland.	The social media-mental health link was moderated by cultural dimensions (e.g., individualism-collectivism).
Global South	Sher Baz Khan (2025)	Review and analysis; focus on digital literacy in LMICs.	High exposure coupled with low algorithmic awareness increases vulnerability.

3.5. Protective Factors and Moderators

Not all adolescents experience negative effects, underscoring the importance of protective moderators. Digital literacy, the ability to critically evaluate online content and understand algorithmic curation, is a significant buffer. Adolescents with higher digital literacy are better equipped to recognize recommendation biases and manage their online experiences (Sher Baz Khan, 2025). Furthermore, strong social support from peers and parents can mitigate the negative impacts of algorithmic exposure (Salerno et al., 2025). On a macro level, policy interventions are emerging as crucial moderators. Regulatory frameworks like the EU's Digital Services Act and the UK's Online Safety Bill aim to enforce greater transparency and accountability from platforms, potentially reducing the amplification of harmful content and protecting vulnerable users (Costello et al., 2024).

4. Methodological Gaps in Global Research

Despite a growing body of literature, significant methodological challenges impede a comprehensive and nuanced understanding of the relationship between algorithmic exposure and adolescent mental health trajectories (Shukla, P., et. al., 2025). These gaps are particularly pronounced when attempting cross-national comparisons and causal inference.

4.1. The Measurement Problem: Proxies Over Precision

The most fundamental challenge is the *operationalization and measurement of algorithmic exposure*. The vast majority of studies, including longitudinal ones, rely on coarse proxies such as total *screen time or frequency of use* (Boers et al., 2019; Liu & Li, 2024). These metrics are insufficient as they fail to capture the qualitative nature of exposure, *what* content is being recommended, *how* it is personalized, and the *intensity* of algorithmic curation. For instance, two adolescents may spend identical time on TikTok, but one may be trapped in a feedback loop of negative content while another engages with educational or prosocial material. Without platform-level data or more sophisticated measurement tools (e.g., digital phenotyping, screenomics), research conflates vastly different experiences, obscuring the unique risk mechanisms of algorithms.

4.2. The Black Box: Lack of Data Access and Transparency

A second, critical barrier is the *opaque nature of platform algorithms*. Social media companies treat their recommendation systems as proprietary secrets, creating a "black box" problem for researchers (Costello et al., 2024). This lack of transparency prevents scientists from:

- **Auditing algorithms** for bias or harmful amplification pathways independently.
- Understanding how **algorithmic changes** over time impact user experience and mental health outcomes (a significant confounder in longitudinal studies).
- Precisely defining the independent variable (algorithmic exposure) in their models.

While audit studies using sock-puppet accounts (UCL, 2024; Baumann et al., 2025) are a innovative workaround, they are resource-intensive and can only simulate, not fully capture, authentic human interaction with the platform.

4.3. The Temporal Gap: Scarcity of Robust Longitudinal Designs

While the field recognizes the need for longitudinal data, there remains a scarcity of studies with **multiple waves, long duration, and large, diverse samples**. Many studies are cross-sectional, capturing a single snapshot in time and precluding any analysis of causal direction or developmental trajectories (Zmavc et al., 2024). Does algorithmic exposure lead to depression, or do depressed adolescents seek out certain types of algorithmic content? Furthermore, few studies track adolescents across critical developmental periods to see how these relationships evolve (Gupta, S., & Mishra, U., 2024). The dynamic and adaptive nature of algorithms themselves, which change in response to user behavior and corporate policy, adds another layer of temporal complexity that is rarely accounted for.

4.4. The Equivalence Challenge: Barriers to Cross-Cultural Comparability

Finally, the quest for a **truly global perspective** is hampered by significant methodological barriers to cross-cultural comparability.

- **Measurement Invariance:** Standardized scales for mental health (e.g., depression, anxiety) or problematic use may not hold the same meaning across different cultures and languages, challenging the validity of direct comparisons (Keles-Gordesli et al., 2025).
- **Digital Infrastructure:** Varying levels of internet access, device ownership, and platform popularity (e.g., dominance of local vs. global platforms) mean that the very nature of "social media use" differs across countries.
- **Cultural Stigma:** Differences in cultural norms and stigma surrounding mental health can influence self-reporting behaviors. Adolescents in some cultures may underreport symptoms due to shame, biasing prevalence estimates and the observed strength of associations (Sher Baz Khan, 2025).

These gaps collectively highlight that current research is often measuring the right problem with the wrong tools. Advancing the field requires innovative methods, greater data transparency from platforms, and dedicated funding for collaborative, multi-national longitudinal cohorts that employ culturally sensitive and technologically precise measures.

5- Proposed Conceptual Framework for Future Research

To address the identified gaps and guide future longitudinal, multi-country investigations, we propose an integrative conceptual framework that moves beyond simplistic models of "screen time" and instead captures the dynamic and multi-layered nature of algorithmic exposure (Gupta, S., 2023). This framework posits that adolescent mental health trajectories are not solely determined by algorithmic inputs but are shaped by a complex interplay of individual usage behaviors, psychological processes, and broader contextual moderators.

5.1- Core Components of the Framework:

Table 3: Components of a Conceptual Framework for Studying Algorithmic Exposure and Adolescent Mental Health Trajectories

S No.	Component Category	Specific Construct	Definition and Operationalization
1	Algorithmic Inputs	Personalization	The degree to which content is curated for the individual user (e.g., perceived algorithm responsiveness; Taylor & Chen, 2024).
		Recommendation Intensity	The frequency and prominence of algorithmically suggested content (e.g., proportion of feed from "For You" vs. "Following") and its nature (e.g., emotional charge, extremeness; Baumann et al., 2025; UCL, 2024).

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		Amplification Dynamics	The speed and scale at which certain content types are promoted through engagement-driven feedback loops.
2.	**Individual Usage Patterns**	Active vs. Passive Use	Passive consumption is often more strongly linked to upward social comparison and internalizing symptoms (Boers et al., 2019).
		Time and Frequency	While a blunt metric, duration and frequency of exposure remain relevant within the context of the other, more nuanced factors
		Platform and Feature Selection	Differential effects may arise from engagement with TikTok's "For You Page" versus Instagram's "Reels" or a chronological friends-only feed.
3.	**Psychological Mediators**	Upward Social Comparison	The tendency to compare oneself to others who are perceived as better off, often triggered by idealized content (Salerno et al., 2025; Yang et al., 2024)
		Fear of Missing Out (FoMO):	The pervasive apprehension that others might be having rewarding experiences from which one is absent, exacerbated by constantly updating feeds.
		Sleep Disruption	Algorithmic designs that promote infinite scrolling can directly encroach on sleep duration and quality, a well-established risk factor for poor mental health.
4.	**Mental Health Outcomes**	trajectories	**Negative Trajectories** The onset, escalation, or persistence of depression, anxiety, loneliness, and low self-esteem.
			Positive Trajectories: The maintenance or improvement of resilience, well-being, life satisfaction, and adaptive coping strategies, even in the face of high exposure (Chen, Done et al., 2021).
5.	**Contextual Moderators**	Cultural Norms	Individualism/collectivism, norms around self-presentation, and stigma regarding mental health (Keles-Gordesli et al., 2025).
		Digital Literacy	The capacity to critically evaluate online content, understand algorithmic curation, and manage privacy settings (Sher Baz Khan, 2025).
		Parental Mediation	○ The strategies parents use to guide and regulate their adolescents' online experiences.
		Socioeconomic Context	Access to resources, alternative activities, and socioeconomic stress.

6- Future Directions

Building upon the identified gaps and the proposed conceptual framework, future research must adopt more rigorous, collaborative, and policy-engaged approaches to effectively understand and mitigate the risks of algorithmic exposure.

6.1. Longitudinal, Multi-Country Studies

There is a pressing need for *large-scale, multi-wave longitudinal studies* that track diverse adolescent cohorts across multiple countries over several years. Such designs are essential for establishing temporal precedence and causal inference, allowing researchers to determine whether algorithmic exposure predicts changes in mental health, or vice versa (Boers et al., 2019; Liu & Li, 2024). These studies must move beyond simplistic metrics and employ nuanced measures of algorithmic exposure (e.g., perceived personalization, device-level tracking of specific features used) to capture the qualitative nature of digital engagement. Crucially, including samples from low- and middle-income countries (LMICs) is necessary to test the generalizability of findings and understand the role of culturally specific moderators (Keles-Gordesli et al., 2025; Sher Baz Khan, 2025).

6.2. Interdisciplinary Approaches

Addressing this complex phenomenon requires *interdisciplinary collaboration* that transcends traditional academic silos. Psychologists and psychiatrists must partner with computational social scientists and data experts to develop innovative methods for auditing algorithms and analyzing large-scale behavioral data (Baumann et al., 2025; Costello et al., 2024). Furthermore, collaboration with educators is key to developing and evaluating digital literacy interventions aimed at building resilience among adolescents. Such a united front is necessary to bridge the gap between identifying algorithmic risks and creating tangible solutions.

6.3. Platform Cooperation and Transparency

A significant barrier to progress is the opaque nature of platform data. Future research impact hinges on *gaining cooperative access* from technology companies (Gupta, S., 2024). Researchers should advocate for access to anonymized, aggregated data on user engagement and algorithmic recommendations through transparent, privacy-protecting partnerships (Costello et al., 2024). Independent audit studies, which have proven effective in revealing amplification patterns (UCL, 2024), should be expanded and systematized. This transparency is a prerequisite for truly understanding the mechanisms linking platform design to user well-being.

6.4. Policy-Relevant Research

Finally, research must be designed with *direct policy implications* in mind. As governments worldwide implement new digital regulations (e.g., the EU's Digital Services Act, the UK's Online Safety Act), researchers have a critical role in providing evidence to evaluate their effectiveness. Studies should be designed to test the impact of specific policy measures, such as age-appropriate design codes, default time limits, and "algorithmic neutrality" options for young users (Costello et al., 2024). The goal is to generate actionable evidence that informs legislators and regulators on how to hold platforms accountable for creating safer online environments for adolescents.

Conclusion

The pervasive integration of AI-driven algorithmic systems into social media platforms has fundamentally altered the digital landscape for adolescents. This review consolidates evidence that algorithmic exposure, defined by personalised curation, recommendation intensity, and amplification dynamics, significantly influences adolescent mental health trajectories, contributing to both negative outcomes like depression and anxiety and positive pathways of resilience and coping (Gupta, S., et. al., 2025). However, the research remains fragmented, often relying on coarse proxies like screen time rather than direct measures of algorithmic influence, and is heavily skewed toward high-income countries, limiting our understanding of global and contextual nuances (Gupta, S., & Singh, V., 2025).

Key psychological mechanisms such as upward social comparison, fear of missing out (FoMO), rumination, and sleep disruption serve as critical mediators in this relationship. These processes are not uniform; they are profoundly shaped by contextual moderators, including cultural norms, digital literacy, parental mediation, and socioeconomic factors. The proposed conceptual framework underscores the necessity of examining these dynamic interactions across different levels, from algorithmic design to individual usage patterns and broader societal contexts.

Moving forward, longitudinal, multi-country studies are essential to trace causal pathways and developmental trajectories. Interdisciplinary collaboration, integrating psychology, data science, and education, is crucial for advancing methodological rigor and innovation. Furthermore, cooperation from social media platforms to provide transparent access to anonymized data is imperative for ethical and effective research. Finally, policy-relevant studies are needed to evaluate regulatory interventions and ensure they are grounded in empirical evidence.

In conclusion, safeguarding adolescent well-being in the digital age requires a global, evidence-based approach that prioritizes nuanced research, cross-sector collaboration, and informed policy-making. By addressing the complexities of algorithmic exposure, we can better support adolescents in navigating the challenges and opportunities of an increasingly personalized digital world

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