

**NAVIGATING THE ALGORITHM
FEED: A CRITICAL MEDIA
LITERACY FRAMEWORK FOR
THE AI ERA**

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Abstract

The proliferation of algorithmic content curation on social media has intensified the spread of AI-driven misinformation, deepfakes, and polarizing narratives. Yet, most formal media literacy curricula remain rooted in static, text-based evaluation techniques that do not account for the speed, scale, and algorithmic opacity of contemporary digital platforms. This paper addresses the critical gap between existing media literacy frameworks and the real-time, user-generated nature of online information environments. Drawing on Kellner and Share's Critical Media Literacy as a theoretical lens, the study argues that traditional approaches focused on verifying source credibility or detecting bias in static messages are insufficient for navigating dynamic, algorithmically curated feeds where content is personalized, ephemeral, and often stripped of provenance cues. Through a conceptual analysis of recent cases involving AI-generated images, viral disinformation campaigns, and echo chamber effects, the paper identifies five specific limitations of current educational models: (1) lack of attention to algorithmic amplification, (2) minimal training on synthetic media detection, (3) passive consumption rather than participatory critique, (4) decontextualized skill exercises, and (5) insufficient focus on affective manipulation. In response, the paper proposes strategic adaptations that integrate platform literacy, real-time verification heuristics, and critical interrogation of recommendation engines. The findings suggest that without updating media literacy for the AI era, even well-educated users remain vulnerable to computational propaganda. This research offers actionable guidelines for educators, curriculum designers, and policymakers seeking to close the literacy gap in high-speed, low-transparency digital ecosystems.

Keywords: Media literacy, Algorithmic curation, AI-driven misinformation, Critical media literacy, Digital technologies.

Introduction

The rapid proliferation of digital media has fundamentally reshaped how individuals access, consume, and interact with information. However, this transformation has been accompanied by an unprecedented rise in AI-driven misinformation, deepfakes, and algorithmically amplified propaganda (Sangwan et al., 2025). Recent data underscores the scale of this phenomenon: by August 2025, leading AI chatbots relayed false claims in 35% of cases, a significant increase from 18% the previous year. Furthermore, a deepfake attack is projected to occur every five minutes, with digital document forgeries increasing by 244% compared to 2023. These developments not only erode public trust in media but also fragment the public sphere by creating echo chambers and filter bubbles that reinforce existing biases (Kellner & Share, 2019; Pariser, 2011).

The concept of critical media literacy, as articulated by Kellner and Share (2019), provides a robust theoretical lens for examining these challenges. Rooted in critical theory, this framework emphasizes analyzing the power dynamics,

ideologies, and socio-political contexts embedded in media texts. It moves beyond traditional literacy's focus on accessing and evaluating static content, advocating instead for a transformative approach that empowers individuals to deconstruct dominant narratives and engage in social justice-oriented media creation. Yet, despite its relevance, existing media literacy curricula remain largely tethered to evaluating static, text-based sources, often overlooking the dynamic, algorithmically curated, and emotionally charged nature of contemporary social media platforms (Nserat, 2025). This strategic gap is widened by the fact that many formal literacy programs do not adequately address the speed and scale of AI-generated content or the opaque mechanisms of algorithmic curation that drive user engagement.

Consequently, this paper addresses the critical disjuncture between established media literacy frameworks and the realities of the AI-mediated information ecosystem. While traditional approaches focus on verifying source credibility, they fail to equip users with the skills necessary to navigate personalized,

ephemeral feeds where content is stripped of provenance and designed for emotional manipulation (Huang & Hu, 2025). Through a conceptual analysis of recent cases involving synthetic media and computational propaganda, this study identifies specific limitations of current educational models, including insufficient attention to algorithmic amplification and a lack of training on real-time verification heuristics. By proposing strategic adaptations that integrate platform-specific literacy and critical interrogation of recommendation engines, this research offers actionable guidelines for educators and policymakers seeking to close the literacy gap in an era of high-speed, low-transparency digital ecosystems.

The novelty of this study lies not simply in describing the dangers of generative AI and deepfakes, a topic already well-trodden in contemporary research, but in exposing why our current educational strategies are failing and offering a new blueprint to fix them. While most existing research focuses on the technological capabilities of AI-driven misinformation, this paper goes a crucial step further by investigating the pedagogical and

theoretical inadequacies of static media literacy models. By cleanly mapping the core problem that static models face from algorithmic manipulation, grounding the study in Kellner and Share's Critical Media Literacy framework, establishing a clear conceptual methodology, and summarising the five specific limitations, this paper provides a fresh and substantial contribution to the field. It argues that true digital literacy is no longer about teaching students to check a box; it means giving learners the tools to decode platform technology in real time and empowering them to create their own counter-narratives rather than just passively scrolling through a curated feed.

The Gap between Traditional Literacy Model and AI-driven Misinformation

The digital information ecosystem has undergone a radical transformation with the rise of algorithmic content curation and generative artificial intelligence. Social media platforms now prioritize engagement-driven algorithms that amplify sensational, polarizing, and often false content, thereby accelerating the formation of echo chambers and filter bubbles (Kellner & Share, 2019; Sunstein, 2017). While these dynamics are well

documented, the gap between formal media literacy education and the real-time, user-generated, algorithmically opaque nature of contemporary platforms remains critically underaddressed. Existing media literacy curricula, even those incorporating digital elements, remain largely rooted in evaluating static, text-based sources, such as news articles or television broadcasts, rather than preparing learners to navigate dynamic, personalized feeds where content is ephemeral, stripped of provenance, and designed for emotional manipulation (Nserat, 2025; Tandoc et al., 2021).

This technological lag has serious consequences. Recent evidence indicates that by August 2025, leading AI chatbots relayed false claims in 35% of cases, up from 18% the previous year, while deepfake attacks are projected to occur every five minutes (Sangwan et al., 2025). Despite this escalation, most media literacy interventions do not teach users how to detect synthetic media, interrogate recommendation engines, or recognize algorithmic amplification as a form of bias. Instead, they emphasize discrete skills such as checking author credentials or cross-referencing static URLs,

competencies that are largely ineffective against AI-generated content that mimics human verisimilitude and spreads virally within seconds (Huang & Hu, 2025; Vosoughi et al., 2018).

Consequently, a critical problem emerges: existing literacy frameworks fail to prepare individuals for the scale, speed, and opacity of AI-driven misinformation. Even well-educated users remain vulnerable to computational propaganda because they lack the conceptual tools to deconstruct how algorithms shape what they see, why certain narratives are amplified, and how synthetic media can fabricate reality. This gap is not merely technical but theoretical. Without updating media literacy for the AI era, educational efforts risk becoming obsolete, leaving citizens unable to discern manipulation from legitimate discourse. Therefore, this paper addresses the urgent need to identify the specific limitations of current models and to propose strategic adaptations that integrate platform literacy, real-time verification heuristics, and critical interrogation of algorithmic curation.

Theoretical Framework

Building on the identified gap between traditional literacy models and AI-driven misinformation, this study adopts Critical Media Literacy (CML) as developed by Kellner and Share (2019) as its primary theoretical lens. This framework is a perfect fit for this study as it allows for a deep exploration of the complex social and political power dynamics that shape modern digital platforms, moving beyond surface-level critiques of new technology. Unlike conventional media literacy approaches that emphasize the neutral acquisition of verification skills, CML is rooted in critical theory and focuses on analyzing the power, ideology, and representation embedded in media texts. It conceptualizes media not as transparent conduits of information but as socially constructed artefacts that serve dominant economic and political interests. According to Kellner and Share (2019), CML comprises four core dimensions: (1) accessing media, (2) analyzing author purpose and audience position, (3) evaluating content for bias and missing perspectives, and (4) producing counter-narratives that challenge hegemony. This framework is particularly suited to examining algorithmic curation because

it encourages users to ask who benefits from amplified content, whose voices are silenced, and how recommendation engines reproduce systemic inequalities. By applying CML, this paper moves beyond skill-based checklists toward transformative strategies capable of addressing the opaque, emotionally manipulative nature of AI-mediated platforms (Mihailidis, 2019; Tuchman, 1978).

Strategic Adaptations to Addressing the Gap between Traditional Literacy Model and AI-driven Misinformation

The analysis yields five interconnected findings that directly address the problem of outdated media literacy frameworks. Each finding identifies a specific limitation of existing models and provides a corresponding strategic adaptation, grounded in critical media literacy (Kellner & Share, 2019), to prepare learners for the scale, speed, and opacity of AI-mediated misinformation. First, algorithmic amplification must be taught as a form of bias. Traditional media literacy teaches students to detect author bias, source reliability, and overt persuasive techniques, but this approach overlooks how recommendation engines,

devoid of human authors, systematically amplify certain content. Effective media literacy must therefore treat algorithmic amplification as a structural bias.

One actionable strategy is to conduct algorithmic audit exercises, where students compare their personalized social media feeds with a logged-out or incognito view of the same platform and document which types of content appear disproportionately, such as outrage-inducing, sensational, or emotionally charged posts. This practice makes the invisible logic of amplification visible (Nserat, 2025). Another method involves reverse engineering "For You" pages using browser extensions or platform transparency tools like TikTok's "Why this video" feature, enabling students to identify which engagement signals likes, watch time, and shares-likely triggered a recommendation. Additionally, case studies of algorithmic harm, such as Facebook's amplification of Myanmar's violence, allow students to map how engagement metrics overrode content moderation, demonstrating that neutral algorithms encode value judgments (Huang & Hu, 2025). This finding directly resolves the problem's first limitation: lack of attention to

algorithmic amplification. Without this shift, learners remain blind to the primary driver of what they see.

Second, synthetic media detection requires multimodal verification heuristics. The problem statement noted that existing curricula provide minimal training on AI-generated images, deepfakes, and voice cloning. Detection must move from "spot the artifact" (e.g., counting fingers) to a systematic, multimodal heuristic that works even when artifacts are absent. One proposed tool is the SIFT-P framework, adapted from Caulfield's SIFT method by adding a fifth step: check provenance metadata. Students learn to use free tools like Forensically or InVID to examine JPEG ghosts, perform error-level analysis, and conduct reverse-image searches with time filters. Another technique is cross-modal consistency checks: for a video claiming a politician said X, students verify whether the audio waveform matches lip movements, whether lighting reflections are consistent, and whether the claimed event appears in independent news archives (Sangwan et al., 2025). Finally, synthetic media "red teams" involve classroom exercises where students produce short

deepfakes using accessible tools (with ethical disclaimers) and then swap to detect each other's forgeries. This experiential learning builds pattern recognition faster than passive lectures. This finding directly counters the problem's assertion that current models fail against AI-generated content, equipping learners with actionable, repeatable skills.

Third, critical literacy must address affective manipulation, not just factual error. Traditional frameworks prioritise truth-value verification, whereas AI-driven misinformation often manipulates emotions, such as outrage, fear, or hope, to bypass rational scrutiny. Media literacy must therefore train users to recognize and regulate emotional engagement as a primary vector of manipulation. One method is affective annotation: when analyzing a viral post, students annotate not only claims but also the emotions they personally feel, such as anger, amusement, or anxiety, and then compare their annotations with peers to identify content designed to trigger specific affective responses (Mihailidis, 2021). Another strategy involves latency interventions, such as implementing a "three-second pause"

before sharing or reacting to any emotionally charged content. During that pause, students ask: "What feeling is this content trying to create? Who benefits if I feel this way?" Additionally, designing counter-narratives through emotional reframing, using Kellner and Share's (2019) production dimension, allows students to create alternative posts that defuse outrage by introducing complexity or humour, thereby practising emotional redirection as a literacy act. This finding addresses the identified gap in the problem regarding affective manipulation: without emotional regulation skills, even factually correct users spread misinformation by reacting before verifying (Phillips et al., 2025; Pennycook & Rand, 2021).

Fourth, platform-specific literacy must replace decontextualized skill drills. Many curricula teach generic advice such as "check the URL" or "look for spelling errors" skills that are often irrelevant on platforms like TikTok, Instagram Reels, or Reddit, where content is ephemeral, user-generated, and stripped of provenance cues. Literacy must be platform-specific, teaching the unique affordances and vulnerabilities of each major environment. A practical approach

involves platform affordance maps: for each platform (X, TikTok, YouTube, Telegram), students create a one-page map showing default content lifespan (e.g., Stories vanish in 24 hours), algorithmic signals (e.g., retweets versus shares), and common manipulation tactics (e.g., reply-thread hijacking on X, duet manipulation on TikTok). Scenario-based simulations also help: students receive a simulated feed using a tool like the "Bad News" game but expanded to mimic a specific platform's interface, and they must navigate a disinformation campaign within that environment, making real-time decisions under time pressure (Huang & Hu, 2025; Roozenbeek & van der Linden, 2019). Cross-platform provenance tracking is another effective exercise: given a viral claim, such as a video of a disaster, students trace its path across platforms, first posted on Telegram, then clipped on X, then re-enacted on TikTok, noting how each platform's features (e.g., lack of edit history on some) obscure or reveal the original context. This finding directly addresses the critique that existing models ignore platform heterogeneity, helping learners develop transferable, context-aware skills.

Fifth, participatory critique and counter-creation are essential, not optional. The problem noted that current literacy often positions students as passive consumers who merely evaluate content created by others. Meaningful literacy requires students to become producers of critical content, using AI tools themselves to expose manipulation and create alternative narratives. One strategy is constructive disinformation design: under controlled ethical guidelines, students use generative AI (e.g., DALL-E, ChatGPT) to create a plausible but false post, and then write a "debunking companion" explaining exactly which cues a literate viewer would notice. This reverses the asymmetry where only bad actors use AI. Another approach is algorithmic accountability campaigns: students produce short videos or infographics that explain a specific algorithm's bias, such as YouTube's up-next recommendations leading to radicalization, and publish these on the same platform, engaging in participatory critique (Kellner & Share, 2019). Additionally, peer-reviewed counter-narrative repositories allow classes to build a shared database of

debunked claims alongside creative counter-narratives in formats like memes, short skits, or infographics. This moves literacy from individual vigilance to collective resilience. This finding addresses the final limitation of passive consumption: when learners produce as much as they consume, they internalise the constructedness of all media, including AI-generated content.

The original problem statement identified five specific limitations of current media literacy models: lack of attention to algorithmic amplification, minimal training on synthetic media, insufficient focus on affective manipulation, decontextualized skill exercises, and passive consumption rather than participatory critique. Each finding above directly targets one or more of these gaps. Algorithmic amplification ignored is addressed by finding one's audits and reverse-engineering; no synthetic media training is countered by finding two's SIFT-P heuristics, red team creation, and cross-modal checks; affective manipulation overlooked is resolved by finding three's annotation, latency interventions, and emotional reframing; decontextualized generic drills are

replaced by finding four's platform affordance maps, simulations, and cross-platform tracing; and passive consumption is transformed by finding five's constructive disinformation design, accountability campaigns, and counter-creation. Together, these findings demonstrate that updating media literacy for the AI era is not merely a matter of adding a module on deepfakes. It requires a fundamental reorientation: from static, text-based verification to dynamic, platform-specific, emotionally aware, and production-oriented critique. When implemented as an integrated curriculum rather than isolated lessons, these adaptations equip learners with the real-time heuristics and critical dispositions necessary to navigate high-speed, low-transparency digital ecosystems (Nserat, 2025; Sangwan et al., 2025). The gap between formal literacy education and AI-driven misinformation is therefore addressable through deliberate pedagogical redesign, as evidenced by the five findings above.

Conclusion

This study set out to address a pressing contemporary challenge: the widening gap between formal media literacy

education and the realities of an AI-driven, algorithmically curated information ecosystem. As documented above, traditional media literacy curricula remain largely rooted in evaluating static, text-based sources such as news articles or television broadcasts. In contrast, today's digital environment is characterised by personalised, ephemeral feeds, synthetic media, and recommendation engines that amplify content based on engagement rather than accuracy. This disconnect leaves even well-educated users vulnerable to AI-generated misinformation, deepfakes, and computational propaganda, as evidenced by recent data showing that leading chatbots relay false claims in 35% of cases and that deepfake attacks are projected to occur every five minutes (Sangwan et al., 2025). The core problem, therefore, is that existing literacy frameworks fail to prepare individuals for the scale, speed, and opacity of contemporary misinformation.

To investigate this problem, the study adopted Critical Media Literacy (CML) as developed by Kellner and Share (2019) as its theoretical lens. Unlike conventional media literacy approaches

that emphasise neutral skill acquisition, CML focuses on analysing the power, ideology, and representation embedded in media texts. It conceptualises media not as transparent conduits of information but as socially constructed artifacts that serve dominant economic and political interests. With its four core dimensions: accessing, analyzing, evaluating, and producing media, CML provides a transformative framework suited to examining algorithmic curation and AI-generated content, because it encourages users to ask who benefits from amplified narratives, whose voices are silenced, and how recommendation engines reproduce systemic inequalities.

The study's findings directly address the stated problem by identifying five specific limitations of current models and proposing corresponding strategic adaptations. First, algorithmic amplification must be taught as a form of bias, using audit exercises, reverse engineering of "For You" pages, and case studies of algorithmic harm to make invisible logics visible (Nserat, 2025). Second, synthetic media detection requires multimodal verification heuristics, such as the SIFT-P framework (with added

provenance checks), cross-modal consistency checks, and red-team creation exercises, moving beyond artifact-spotting to systematic analysis (Huang & Hu, 2025). Third, critical literacy must address affective manipulation, not just factual error, through affective annotation, latency interventions (e.g., a three-second pause), and counter-narrative design that reframes emotional responses (Mihailidis, 2021; Phillips et al., 2025). Fourth, platform-specific literacy must replace decontextualized generic drills, employing affordance maps, scenario-based simulations, and cross-platform provenance tracking to equip learners with context-aware skills. Fifth, participatory critique and counter-creation are essential, not optional, meaning students should engage in constructive disinformation design, algorithmic accountability campaigns, and peer-reviewed counter-narrative repositories, thereby transforming from passive consumers into active producers of critical content (Kellner & Share, 2019).

Together, these findings demonstrate that updating media literacy for the AI era

requires a fundamental reorientation: from static, text-based verification to dynamic, platform-specific, emotionally aware, and production-oriented critique. The synthesis shows that one or more findings directly address each limitation identified in the problem statement. When implemented as an integrated curriculum rather than isolated lessons, these strategic adaptations equip learners with the real-time heuristics and critical dispositions necessary to navigate high-speed, low-transparency digital ecosystems.

The gap between formal literacy education and AI-driven misinformation is not insurmountable. By grounding media literacy in critical theory and embracing strategies that treat algorithmic amplification as bias, synthetic media as detectable through multimodal heuristics, emotional manipulation as a primary vector, platform specificity as essential, and production as integral to critique, educators can prepare citizens for the challenges of the AI-mediated public sphere. Future research should empirically test these adaptations across different age groups and platforms, and

policymakers should consider mandating updated literacy standards that reflect the realities of algorithmic curation. Ultimately, this study offers an actionable roadmap for closing the literacy gap, one that recognizes that, in an era of deepfakes and recommendation engines, being media literate means not only verifying facts but also interrogating the very architectures that shape what we see and feel.

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