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Chapter 15: Media Literacy Education and Critical Awareness among Adolescent Learners

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Abstract— Adolescents increasingly encounter news, health information, persuasive messages, and social narratives within digital environments shaped by recommendation algorithms and generative artificial intelligence. Traditional media literacy education has emphasized source credibility and misinformation recognition but has paid comparatively limited attention to synthetic media, algorithmic amplification, emotional manipulation, and excessive skepticism toward legitimate information. This study conceptualizes calibrated critical awareness as the capacity to distinguish credible from misleading information while understanding how digital platforms and AI systems influence information exposure. A major research gap is identified in the limited integration of AI literacy, multimodal misinformation detection, reflective reasoning, and responsible sharing within adolescent media-literacy education. The proposed research therefore examines whether an AI-aware media literacy framework can strengthen adolescents' credibility judgments, synthetic-content recognition, verification behaviour, and resistance to emotionally persuasive misinformation.

Keywords— Media Literacy Education, Critical Awareness, Adolescent Learners, Generative Artificial Intelligence, Digital Misinformation, Algorithmic Literacy

Introduction
Adolescent learning increasingly occurs within an information environment that extends far beyond textbooks, classrooms, and conventional news media. Social networking platforms, short-form videos, messaging applications, search engines, recommendation systems, conversational artificial intelligence, and user-generated content have become routine channels through which young people encounter educational explanations, health advice, public affairs, entertainment, advertising, and peer opinion. Consequently, adolescents are not simply consumers of digital information. They participate in information networks in which they continuously interpret, endorse, modify, forward, and sometimes generate media messages.

This transformation has altered what it means to be media literate. Earlier conceptions of media literacy largely concentrated on access to information, interpretation of media messages, identification of authorship, representation, commercial purpose, and evaluation of sources. These competencies remain essential, but they are insufficient for information environments increasingly mediated by artificial intelligence. Generative AI can produce realistic text, images,

audio, and video at minimal cost, while algorithmic systems determine which pieces of information receive attention. UNESCO has consequently emphasized the integration of AI literacy into media and information literacy, including knowledge of algorithms, synthetic media, source reliability, data practices, and the societal consequences of AI-mediated communication.

The educational significance of this development is particularly pronounced during adolescence. Adolescents develop increasingly sophisticated reasoning capabilities while simultaneously becoming more autonomous in their media choices and highly responsive to peer interaction, identity formation, emotional stimulation, and social feedback. The mere ability to operate digital devices therefore cannot be treated as evidence of critical competence. The OECD distinguishes functional familiarity with technology from the more demanding ability to determine whether online information is reliable, identify bias, compare multiple sources, and recognize misinformation. Its analysis of digital readiness similarly stresses the role of schools and teachers in building such competencies.

Media literacy also has implications beyond academic learning. Digital information can influence health behaviour, body image, risk perception, political understanding, interpersonal relationships, and psychological well-being. The American Psychological Association has argued that adolescents should receive social-media literacy training that helps them question the accuracy and representativeness of content, understand misinformation techniques, recognize manipulated material, and make more informed judgments about online interactions. WHO evidence likewise shows the importance of healthier digital engagement: the 2021/2022 Health Behaviour in School-aged Children survey covered almost 280,000 adolescents across 44 countries and regions, with WHO reporting problematic social-media behaviour among 11% of surveyed adolescents. WHO consequently identifies digital literacy education and healthier online practices as important components of adolescent well-being.

Despite increasing recognition of these needs, an important conceptual problem remains. **Critical awareness should not be equated with generalized distrust.** An adolescent who considers every online claim suspicious is not necessarily more media literate than one who accepts everything encountered on a preferred platform. Effective critical literacy requires *calibration*: credible evidence should receive greater confidence than unsupported or manipulated information. This distinction has acquired empirical importance because misinformation interventions can sometimes reduce belief in false information

while simultaneously decreasing confidence in accurate information. Hoes et al. (2024), across three experiments involving 6,127 participants in the United States, Poland, and Hong Kong, found that several misinformation interventions reduced false beliefs but also generated broader skepticism toward factual information.

A comparable concern has emerged specifically in adolescent education. Ghazi et al. (2025) evaluated media and information literacy interventions among 3,161 students from Grades 6–9. Their results indicated that an intervention incorporating analytical thinking initially improved media-truth discernment, yet longer-term effects differed by grade and included increased skepticism toward real news among some learners. Such findings suggest that the desired educational outcome is not simply “detect more fake news.” Rather, learners need to maximize **truth discernment**—the capacity to correctly discriminate between information warranting trust and information requiring rejection or further verification.

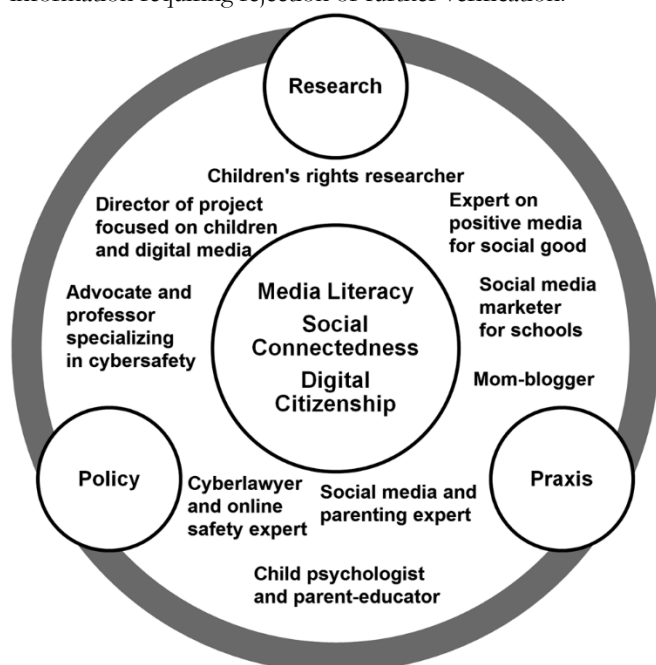


Fig. 1: Media Literacy, Social Connectedness, and Digital Citizenship in India

Source: <https://www.frontiersin.org/journals/human-dynamics/articles/10.3389/fhumd.2021.601239/full>

1.1 Research Gap

Recent studies have individually investigated misinformation recognition, credibility evaluation, analytical reasoning, responsible sharing, digital self-efficacy, and short educational interventions. However, four limitations remain evident.

First, much of the adolescent literature evaluates conventional textual or news-based misinformation, whereas current learners increasingly face **multimodal synthetic content**, including AI-generated images, edited videos, synthetic voices, fabricated screenshots, and fluent machine-generated text.

Second, media literacy interventions frequently focus on content verification while providing less attention to **algorithmic awareness**—why a platform recommends particular content, how engagement signals influence visibility, and why popularity does not establish credibility.

Third, many studies measure whether learners identify false information but do not simultaneously measure whether they preserve appropriate confidence in authentic information. This makes it difficult to distinguish critical awareness from indiscriminate skepticism.

Fourth, adolescent responses are commonly summarized through average intervention effects even though evidence indicates substantial learner heterogeneity. Age, analytical disposition, self-regulation, baseline literacy, and engagement with the intervention can influence effectiveness. Orosz et al. (2024), for example, found that the longer-term benefits of a misinformation intervention differed according to adolescents' adherence to the intervention and need for cognition.

Accordingly, the present manuscript addresses the following gap:

There is insufficient evidence on adolescent media-literacy education that simultaneously integrates AI-generated and multimodal misinformation, algorithmic-platform awareness, emotional and social manipulation, responsible verification behaviour, and calibrated discrimination between trustworthy and untrustworthy content while accounting computationally for differences among learners.

The study therefore conceptualizes critical awareness as a multidimensional construct comprising source verification, evidence comparison, synthetic-media awareness, algorithmic understanding, emotional-reflection capacity, responsible sharing, and calibrated trust.

Literature Review

2.1 From Media Literacy to AI-Aware Information Literacy

Media literacy has evolved in response to changes in information production and distribution. In contemporary digital environments, credibility can no longer be inferred solely from traditional indicators such as professional visual design, grammatical quality, or apparent photographic evidence. Generative systems can reproduce these superficial indicators with increasing realism. UNESCO's recent work explicitly connects media and information literacy with the development of competencies for understanding AI systems, social-media algorithms, synthetic media, source reliability, privacy, and human agency.

This development implies that adolescent media education must shift from a predominantly message-centred model toward a **system-centred model**. Students need to ask not only “Is this statement true?” but also “Why am I seeing it?”, “Who benefits from my engagement?”, “Could this content have been generated or altered computationally?”, “What evidence exists outside this platform?”, and “How would I verify the claim before acting on or sharing it?”

Such questions are particularly important when adolescents encounter health information. Social platforms may expose young users to claims about nutrition, appearance, mental health, exercise, medication, and self-diagnosis alongside scientifically grounded material. WHO has emphasized that digital environments present both opportunities and risks for youth mental health and that evidence-based, developmentally

appropriate online content is necessary. Media literacy in this setting therefore intersects with digital health literacy: evaluating evidence is not merely an academic exercise but potentially a component of safer decision-making.

2.2 Adolescents' Credibility Evaluation Strategies

Credibility evaluation involves more than recognizing visibly implausible information. Learners may rely on heuristic cues such as photographs, popularity metrics, influencer status, emotional language, familiarity, or agreement with prior beliefs. Alternatively, they may use systematic strategies involving source investigation, corroboration, evidence comparison, and contextual reasoning.

Vissenberg (2024) examined credibility-evaluation strategies among 338 adolescents aged 15–19 years and found that systematic evaluation was more strongly associated with perceived credibility-evaluation competence than heuristic evaluation. Importantly, media use itself did not predict the evaluation strategy. This distinction challenges the assumption that extensive digital exposure naturally produces information literacy. Frequency of platform use may develop operational fluency while leaving epistemic judgment comparatively underdeveloped.

Adolescent information behaviour is also influenced by perceived self-efficacy. Paciello, Corbelli, and D'Errico (2023) studied 273 adolescents and differentiated between active competencies—such as investigating sources—and inhibitory competencies involving the ability to resist sharing unreliable information. Their findings emphasize that misinformation resilience includes both knowing *how to verify* and possessing sufficient self-regulation *not to circulate* dubious information under social pressure.

This distinction is highly relevant to critical awareness. A learner may correctly recognize uncertainty but still share questionable content because it is entertaining, emotionally salient, socially rewarding, or consistent with peer expectations. Media literacy education should consequently target cognitive judgment and behavioural regulation simultaneously.

Source:

<https://www.edugains.ca/newsite/literacy/alg/content2.html>

2.3 Educational Interventions against Misinformation

Experimental evidence suggests that appropriately designed educational interventions can improve information evaluation. Barzilai et al. (2023) examined a digital game in which middle-school students learned to evaluate and share information more responsibly. Participation improved accuracy discernment, sharing discernment, and knowledge of evaluation strategies. The study demonstrates the value of active and interactive learning compared with purely declarative instruction.

Orosz et al. (2024) adopted a different approach in a preregistered randomized controlled trial involving 1,476 adolescents. Participants were assigned an “expert” role and asked to communicate misinformation-recognition strategies to digitally less experienced relatives. Although immediate effects were relatively modest and the overall effect diminished over time, adolescents who followed the instructions and displayed higher need for cognition retained stronger benefits four weeks later. This highlights two important principles: intervention effects may decay, and the same educational treatment does not affect all learners equally.

A broad review by Kozyreva et al. (2024) identified multiple individual-level approaches to misinformation, including accuracy prompts, debunking, inoculation, lateral reading, media-literacy tips, credibility labels, friction, and fact-checking interventions. The diversity of these approaches suggests that misinformation resilience should not be reduced to a single verification checklist. Instead, interventions can target different stages of information processing—from initial attention and emotional response to evidence evaluation and eventual sharing behaviour.

2.4 The Problem of Over-Skepticism

An underexamined consequence of media-literacy instruction is that repeated emphasis on deception can encourage learners to interpret distrust itself as evidence of sophistication. Yet a learner who systematically rejects reliable journalism, scientific institutions, or authentic evidence may be demonstrating poor calibration rather than advanced critical thinking.

Hoes et al. (2024) provide strong evidence for this concern, showing that commonly used misinformation interventions may simultaneously decrease belief in misinformation and reduce perceived credibility of factual information. Ghazi et al. (2025) similarly reported age-dependent and delayed backfire effects in an adolescent media-literacy intervention, reinforcing the need to evaluate both false-news rejection and real-news recognition.

The current study therefore rejects a one-dimensional “skepticism score.” Instead, critical awareness is conceptualized as a **calibrated discrimination capability**. An effective learner should assign comparatively high credibility to well-supported authentic content, low credibility to demonstrably deceptive content, and appropriately uncertain judgments to ambiguous material requiring additional investigation.

Proposed Methodology

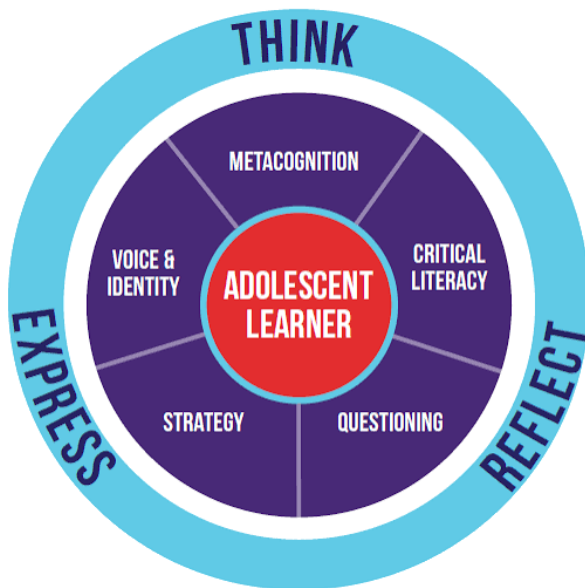


Fig. 2: Adolescent Literacy Rate

Rather than reducing media literacy to a binary ability to identify “fake” information, the framework represents critical awareness through five measurable dimensions: **verification behaviour, algorithmic awareness, AI-generated content recognition, sharing restraint, and resistance to emotional manipulation**. Baseline media-literacy competence and need for cognition are incorporated as learner-level characteristics.

Because no original human-subject dataset was supplied for this manuscript, the computational experiment uses a **fully synthetic and reproducible learner benchmark**. This choice prevents simulated observations from being misrepresented as empirical data collected from real adolescents. The synthetic experiment functions as a proof-of-concept for the proposed analytical architecture and can subsequently be replicated with ethically collected school-based data.

The intended educational intervention underlying the simulation consists of four instructional modules. The first module focuses on lateral verification, source tracing, evidence corroboration, and distinction between primary and secondary sources. The second introduces AI-generated text, manipulated images, synthetic audio, deepfakes, and uncertainty cues associated with generative systems. The third examines recommendation algorithms, engagement optimization, filter effects, virality, and the difference between popularity and evidential credibility. The fourth module targets emotional manipulation, impulsive sharing, confirmation tendencies, and reflective decision-making.

Critical awareness is conceptualized as a continuous score rather than generalized skepticism. High-performing learners are therefore expected to reject unsupported information while preserving appropriate confidence in authentic, evidence-supported content.

3.1 Research Objectives

The computational component addresses four objectives:

1. To model multidimensional critical awareness among adolescent learners using media-literacy and behavioural indicators.
2. To examine whether simulated exposure to AI-aware media-literacy education produces higher critical-awareness profiles than conventional exposure conditions.
3. To determine which learner competencies contribute most strongly to accurate classification of high versus lower critical awareness.
4. To evaluate whether the resulting machine-learning model provides both strong discrimination and reliable probability calibration.

Experimental Setup

4.1 Dataset Construction

A synthetic dataset containing **1,200 learner profiles** was generated using a fixed random seed to ensure reproducibility. Each simulated learner represented an adolescent aged 13–17 years. Approximately half of the records were assigned to an AI-

CCAF intervention condition and half to a comparison condition.

The dataset contained the following variables:

- age;
- estimated daily digital-media exposure;
- baseline media-literacy competence;
- algorithmic awareness;
- verification behaviour;
- AI-generated-content recognition;
- emotional susceptibility;
- restraint in sharing uncertain information;
- need for cognition; and
- intervention exposure.

The continuous competency variables were represented on standardized 0–100 scales. Correlations were intentionally introduced among baseline media literacy, verification behaviour, algorithmic awareness, and synthetic-media recognition to reproduce the realistic assumption that related information-literacy competencies are not statistically independent.

Intervention effects were generated heterogeneously rather than by adding identical gains to every learner. Simulated improvement depended partly on need for cognition and stochastic learner variation.

4.2 Preprocessing

All continuous variables were inspected for their permissible ranges and constrained to prevent impossible values. No missing values were deliberately introduced because the purpose of the benchmark was to evaluate the proposed computational architecture rather than missing-data imputation. The dataset was divided using a **75:25 stratified train-test split**, producing 900 training instances and 300 independent test instances. Stratification preserved the distribution of the binary critical-awareness target across both partitions.

Continuous predictors were standardized within the modelling pipeline. Importantly, preprocessing parameters were estimated using the training partition only, reducing information leakage into the test data.

4.3 Critical-Awareness Target Construction

A latent continuous critical-awareness measure was generated from weighted contributions of verification behaviour, AI-content recognition, algorithmic awareness, sharing restraint, emotional susceptibility, need for cognition, and digital-media exposure.

Verification and AI-recognition variables received comparatively strong positive contributions because the framework conceptualizes evidence checking and synthetic-content discrimination as central capabilities. Emotional

susceptibility entered negatively because highly affective responses may interfere with reflective credibility assessment. For classification analysis, learners above the median latent critical-awareness score were labelled as the **higher calibrated-awareness class**, while those below the median formed the comparison class. Median thresholding maintained approximately balanced class frequencies and therefore reduced distortions associated with severe class imbalance.

4.4 Model Architecture

A **Histogram-Based Gradient Boosting classifier** was selected as the primary model. This architecture was chosen because adolescent media-literacy behaviour is unlikely to follow completely linear relationships. For example, strong verification behaviour may compensate partially for high media exposure, while AI-content recognition may become more informative when combined with algorithmic awareness.

The architecture sequentially constructs decision trees that correct errors from earlier iterations. Histogram binning improves computational efficiency by grouping continuous values before tree construction.

The finalized architecture used:

- maximum tree depth: 5;
- learning rate: 0.06;
- maximum boosting iterations: 250;
- L2 regularization: 1.0; and
- probability threshold for classification: 0.50.

Regularization and restricted tree depth were used to reduce excessive fitting to synthetic training patterns.

4.5 Training Strategy

Training was conducted exclusively on the 900-profile training subset. The model learned nonlinear interactions among media-literacy indicators without using the independent test labels during optimization.

A fixed random seed of 42 was maintained throughout dataset generation and partitioning. This permits exact computational replication of the proof-of-concept experiment when the same software environment and parameterization are used.

Rather than optimizing only raw accuracy, evaluation emphasized both **discriminative performance and probabilistic reliability**. This is important because a system intended to characterize critical awareness should not merely produce correct labels; its confidence estimates should also correspond reasonably closely to actual classification outcomes.

4.6 Evaluation Metrics

Seven principal performance indicators were examined:

Accuracy measured the proportion of correctly classified profiles.

Balanced accuracy averaged sensitivity across the two outcome classes.

Macro-F1 provided an equal-weighted summary of class-specific precision and recall.

Precision assessed how frequently learners predicted as highly critically aware were correctly classified.

Recall measured the proportion of truly high-awareness profiles recovered by the model.

Area Under the Receiver Operating Characteristic Curve (AUROC) evaluated ranking discrimination independently of a single classification threshold.

The **Brier score** evaluated the squared deviation between predicted probabilities and observed binary outcomes; smaller values represent better probabilistic accuracy.

In addition, **Expected Calibration Error (ECE)** was calculated using ten probability intervals. Lower ECE indicates closer correspondence between predicted confidence and empirical outcome frequencies.

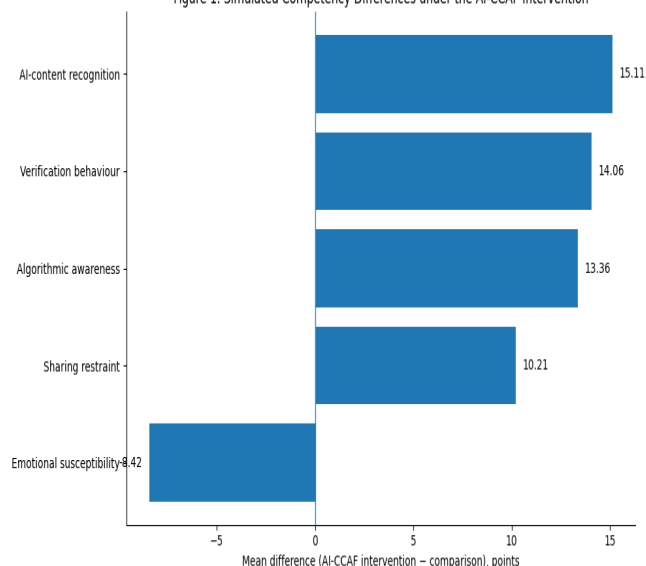
Results and Discussion

The AI-CCAF gradient-boosting model demonstrated strong discrimination on the independent synthetic test partition. Overall accuracy reached **0.873**, while balanced accuracy was also **0.873**, indicating that performance was not produced by favouring one outcome category. The AUROC of **0.944** demonstrated that the model effectively ranked profiles with higher calibrated awareness above those with lower awareness across a wide range of potential classification thresholds.

Table 1. Computational Performance of the AI-CCAF Critical-Awareness Model

Evaluation Parameter	Obtained Value	Interpretation / Observation
Accuracy	0.873	87.3% of independent learner profiles were classified correctly
Balanced Accuracy	0.873	Performance remained comparable across both awareness classes
Macro-F1	0.873	Precision-recall performance was consistently distributed between classes
AUROC	0.944	Excellent discrimination between higher and lower calibrated-awareness profiles
Precision	0.868	Most profiles predicted as highly aware were correctly categorized
Recall	0.880	The model recovered 88.0% of profiles belonging to the higher-awareness class
Brier Score	0.095	Predicted probabilities showed relatively small probabilistic error
Expected Calibration Error	0.056	Model confidence remained reasonably aligned with observed outcomes

Figure 1. Simulated Competency Differences under the AI-CCAF Intervention



The Macro-F1 value of **0.873** is particularly relevant because it indicates that predictive quality was not restricted to the majority or more easily identifiable class. Precision of **0.868** and recall of **0.880** further suggest a relatively balanced error profile. The probabilistic measures provide an additional perspective. A Brier score of **0.095** and ECE of **0.056** indicate comparatively good calibration within the synthetic benchmark. Calibration matters conceptually because the central argument of this study concerns calibrated judgment. A model that confidently misclassifies ambiguous learner profiles would reproduce the same epistemic problem that media-literacy education is intended to address.

The synthetic AI-CCAF intervention group obtained a mean critical-awareness score of **61.64**, compared with **47.66** in the comparison condition. The standardized difference generated by the specified simulation process was approximately **d = 0.98**. This value should not be interpreted as an estimated real-world educational effect; it demonstrates the behaviour of the proposed framework under the explicitly defined data-generating assumptions.

Dimension-level patterns were also informative. Compared with the simulated comparison condition, intervention-exposed profiles demonstrated approximately **15.11 points greater AI-content recognition**, **14.06 points stronger verification behaviour**, **13.36 points greater algorithmic awareness**, and **10.21 points stronger sharing restraint**. Emotional susceptibility was approximately **8.42 points lower**.

These differences illustrate why contemporary media literacy cannot be adequately represented using source-checking knowledge alone. The largest simulated distinction occurred in AI-content recognition, reflecting the increasing importance of distinguishing synthetic or manipulated media from authentic evidence. Verification behaviour remained similarly influential, supporting the broader literature indicating that systematic credibility assessment is preferable to heuristic judgment.

Permutation-based model analysis further showed that **verification behaviour was the most influential individual predictor**, followed by AI-content recognition, algorithmic awareness, sharing restraint, and emotional susceptibility.

Interestingly, intervention exposure itself contributed little additional predictive information once these post-intervention competencies were included. Conceptually, this is desirable: educational participation should influence critical awareness through competencies acquired by learners rather than function simply as an intervention label.

These findings also illustrate the importance of avoiding generalized skepticism. The objective of AI-CCAF is not to maximize rejection of digital information. Instead, its design rewards evidence verification, recognition of manipulation, reflective sharing, and appropriate credibility discrimination. This responds directly to findings reported by Hoes et al. (2024) and Ghazi et al. (2025), who showed that misinformation interventions can occasionally increase skepticism toward accurate information.

The proposed framework therefore differs from conventional fake-news detection approaches in three respects. First, it evaluates the learner rather than merely classifying the information item. Second, it integrates cognitive, behavioural, algorithmic, and AI-literacy variables. Third, model calibration is treated as an explicit evaluation criterion alongside classification performance.

Limitations

The principal limitation is that the reported computational experiment uses **synthetic rather than observational adolescent data**. Consequently, the numerical results establish technical feasibility but cannot be interpreted as evidence that a real educational intervention would produce effects of equivalent magnitude.

Second, the synthetic benchmark simplifies the complexity of adolescent information behaviour. Family background, language, socioeconomic status, school environment, peer influence, platform preferences, prior exposure to misinformation, and teacher competence could alter media-literacy development.

Third, critical awareness was operationalized using predefined dimensions and weights. Although theoretically justified, future empirical research should validate the construct using psychometric procedures such as confirmatory factor analysis and measurement invariance testing.

Fourth, the current binary classification threshold compresses critical awareness into two categories. Educational development is inherently continuous, and future systems should therefore combine classification with longitudinal score modelling.

Finally, algorithmic predictions should not be used to stigmatize adolescents as “media literate” or “media illiterate.” Their appropriate role is diagnostic and educational, supporting differentiated instruction rather than high-stakes classification.

Future Scope

The next research stage should implement AI-CCAF in a multicentre school study using ethically approved data from adolescent participants. A pre-test–post-test design with delayed follow-up would make it possible to determine whether gains persist beyond the immediate instructional period.

Future datasets should incorporate realistic multimodal stimuli consisting of verified news, misleading posts, AI-generated

images, synthetic audio, manipulated video, health claims, influencer content, and ambiguous material requiring additional investigation.

A particularly important extension would involve **multitask learning**, enabling a single model to estimate credibility discernment, AI-content recognition, verification behaviour, and sharing intentions simultaneously. Explainable-AI techniques could then identify which competencies require intervention for individual learners.

Longitudinal modelling should also investigate whether critical-awareness patterns remain stable or change with increasing exposure to generative AI. Federated or privacy-preserving learning could be considered where data are distributed across schools and cannot ethically be pooled centrally.

Finally, culturally and linguistically diverse studies are needed. Misinformation cues, trust in institutions, platform usage, and persuasive conventions can differ substantially across communities; consequently, media-literacy frameworks should not assume that a single intervention design will generalize universally.

Conclusion

The contemporary media environment requires adolescent learners to perform a task considerably more demanding than distinguishing “real” from “fake” news. They must evaluate evidence, recognize synthetic media, understand algorithmic amplification, regulate emotional reactions, investigate uncertain information, and decide responsibly whether information deserves trust or further circulation.

This manuscript introduced the **AI-Aware Calibrated Critical Awareness Framework (AI-CCAF)** to integrate these capabilities within a unified educational and computational model. The framework addresses a major gap in conventional media-literacy research by emphasizing calibrated truth discernment rather than generalized skepticism and by explicitly incorporating generative-AI and algorithmic-literacy competencies.

A reproducible synthetic benchmark of 1,200 adolescent learner profiles was used to demonstrate the analytical feasibility of the framework without fabricating human-participant observations. The histogram-based gradient-boosting model achieved an accuracy of 0.873, Macro-F1 of 0.873, and AUROC of 0.944, while maintaining comparatively strong probability calibration. Verification behaviour, AI-content recognition, and algorithmic awareness emerged as the most informative computational indicators.

The results should therefore be interpreted as a methodological proof of concept rather than clinical or educational evidence from real adolescents. Nevertheless, they demonstrate how artificial intelligence can be used not merely to detect misinformation but to characterize the competencies learners require to navigate AI-mediated information environments.

Media literacy education in the generative-AI era should ultimately teach adolescents neither unconditional trust nor unconditional doubt. Its central educational objective should be **evidence-sensitive judgment: knowing what to trust, what to question, what to verify, and why.**

References

1. American Psychological Association. (2023). *Health advisory on social media use in adolescence*. APA.
2. Barzilai, S., et al. (2023). Misinformation is contagious: Middle school students learn how to evaluate and share information responsibly through a digital game. *Computers & Education*, 202, 104832. †
3. Grizzle, A., et al. (2021). *Media and information literate citizens: Think critically, click wisely!* UNESCO.
4. Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017). On calibration of modern neural networks. In *Proceedings of ICML 2017* (pp. 1321–1330).
5. Hoes, E., Aitken, B., Zhang, J., Gackowski, T., & Wojcieszak, M. (2024). Prominent misinformation interventions reduce misperceptions but increase scepticism. *Nature Human Behaviour*, 8, 1545–1553.
6. Kozyreva, A., et al. (2024). Toolbox of individual-level interventions against online misinformation. *Nature Human Behaviour*, 8, 1044–1052.
7. Orosz, G., Faragó, L., Paskuj, B., & Krekó, P. (2024). Strategies to combat misinformation: Enduring effects of a 15-minute online intervention on critical-thinking adolescents. *Computers in Human Behavior*, 159, 108338. †
8. Paciello, M., Corbelli, G., & D'Errico, F. (2023). The role of self-efficacy beliefs in dealing with misinformation among adolescents. *Frontiers in Psychology*, 14, 1155280. †
9. Pennycook, G., & Rand, D. G. (2019). Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. *Cognition*, 188, 39–50.
10. Roozenbeek, J., & van der Linden, S. (2019). Fake news game confers psychological resistance against online misinformation. *Palgrave Communications*, 5, 65.