

The Transformation of Educational Media in the Age of the Algorithm Generation: Adapting Learning to an AI-Based Digital Ecosystem

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ABSTRACT: The rapid advancement of artificial intelligence has fundamentally changed how young people access information and interact with digital technology, giving rise to the term “algorithm generation” a generation whose thinking patterns, preferences, and learning habits are substantially shaped by automated recommendation and content-curation systems. This study addresses three research questions: (1) how educational media is transforming in response to the algorithm generation’s cognitive-behavioral formation; (2) what learning-adaptation strategies are needed for this transformation to move toward augmentation and redefinition rather than inversion of learning; and (3) what challenges accompany this shift and how a human-centered approach can mitigate them. The novelty of this study lies in explicitly positioning “algorithm generation” as an analytic construct rather than an uncritical generational label and in building an integrative conceptual framework linking learners’ cognitive formation, educational media transformation, and multi-level adaptation strategies (teachers, learners, curriculum), an integration rarely found in existing AIED (artificial intelligence in education) reviews, which tend to remain fragmented. The study adopts a qualitative approach with a systematic-integrative literature review design: identification, screening, and eligibility procedures follow PRISMA 2020 logic across 22 primary sources, followed by critical-comparative thematic synthesis. Findings show that educational media is shifting from a static, one-way model toward an adaptive, personalized, data-driven model, yet the direction of this shift toward augmentation/redefinition or toward inversion of learning depends heavily on how seriously adaptation strategies and human-centered, critical, and ethical AI design are actually implemented. This study recommends that the development of educational media in Indonesia explicitly integrate this conceptual framework, particularly during the transition from Kurikulum Merdeka toward deep-learning pedagogy.

KEYWORDS: algorithm generation; educational media transformation; conceptual framework; artificial intelligence; systematic-integrative literature review

I. INTRODUCTION

The everyday lives of today’s young people unfold within a digital environment that is, to a considerable extent, governed by algorithms. Each time a user opens a social media application, watches a video, or searches for information, the artificial intelligence system operating behind the platform silently determines which content appears on the screen, drawing on that user’s behavioral trace. Brady et al. (2023) demonstrate that human social learning now largely takes place through online platforms whose algorithms are optimized to sustain user attention and engagement rather than to ensure the accuracy or utility of the information disseminated. This condition has gradually come to shape the thought patterns, preferences, and even the learning habits of the generation that has grown up alongside it.

Two decades ago, Prensky (2001) introduced the term “digital natives” to describe a generation born and raised amid digital technology, whose members, he argued, think and process information differently from previous generations. That term is worth extending to today’s artificial-intelligence context, but such an extension must be undertaken with caution. Bennett et al. (2008) caution that claims about digital generations frequently outrun the available empirical evidence and risk hardening into a form of academic “moral panic.” Taking this critique to heart, the present article does not treat “algorithm generation” as a settled generational label but rather as an explicitly constructed analytic construct elaborated in full in Section 3 used to designate learners whose preferences, attention spans, and ways of engaging with information are, in part, shaped by the algorithmic logic of the digital platforms they use daily.

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This shift on the learner's side presents education with both a challenge and an opportunity. On one hand, conventional educational media static, uniform, and one-directional risk finding it increasingly difficult to capture the attention of learners accustomed to personalized content and instant feedback. On the other hand, the very personalization logic that has shaped the habits of the algorithm generation can now be harnessed pedagogically. A range of systematic reviews indicates that artificial intelligence has driven the development of adaptive learning systems capable of tailoring content, pacing, and presentation style to each learner's needs in real time (Zawacki-Richter et al., 2019), a trend reaffirmed with a substantially more current scope that incorporates advances in generative artificial intelligence by a recent systematic review of personalized-learning terminology in the AI era (Khalifeh et al., 2026).

Concern over the influence of algorithms on how young people view information is not merely normative discourse; it has been demonstrated quantitatively at scale. Bakshy et al. (2015), analyzing more than ten million Facebook users, found that algorithmic ranking reduced users' exposure to cross-cutting content by approximately 15 percent, although individual choice itself proved to exert an even stronger constraining effect than the algorithm. This finding matters for the present study because it shows that algorithmic curation and user agency jointly shape how the algorithm generation consumes information a nuance that must be preserved so that the algorithm generation is not understood in purely deterministic terms as the passive victim of algorithms. At roughly the same time, Indonesian education has been undergoing a pedagogical transformation through deep-learning policy that reinforces the Kurikulum Merdeka (Kemendikdasmen, 2024, 2025). It is precisely this convergence between learners shaped by an algorithmic ecosystem and a curriculum-policy direction that demands more meaningful learning that makes a study of educational media transformation feel urgent.

A substantial body of international scholarship has mapped the application of artificial intelligence in education broadly, spanning intelligent tutoring systems, learning analytics, and AI literacy for learners (Casal-Otero et al., 2023; Zawacki-Richter et al., 2019). A review of reviews conducted by Mustafa et al. (2024) on the AIED research landscape, however, concludes that the field remains fragmented into isolated traditions, methodologies, and subtopics, underscoring the need for a more comprehensive perspective capable of synthesizing this scattered evidence. This gap becomes even more apparent given how few studies explicitly connect the cognitive and behavioral shifts of the algorithm generation to the need for a comprehensive redesign of educational media, particularly within the Indonesian context currently undergoing curriculum transition. Most national studies continue to focus narrowly on the partial adoption of AI tools or on teacher readiness alone, without fully situating these issues within a more holistic learning-ecosystem framework.

Given this gap, the novelty of the present study rests on three grounds. First, it positions "algorithm generation" as an explicitly defined and theoretically accountable analytic construct extending the notion of "digital natives" (Prensky, 2001) while preserving the epistemic caution urged by Bennett et al.'s (2008) critique rather than treating it as a taken-for-granted generational label. Second, rather than mapping AI applications or literacy frameworks in isolation, as is common in prior AIED systematic reviews (Casal-Otero et al., 2023; Zawacki-Richter et al., 2019), this study proposes an integrative conceptual framework that explicitly links learners' cognitive-behavioral formation, the transformation of educational media, and multi-level adaptation strategies (teachers, learners, curriculum) an integration that Mustafa et al. (2024) identify as still rarely undertaken in a unified manner. Third, the study situates this global conceptual synthesis within the policy context of deep learning and the Kurikulum Merdeka in Indonesia (Kemendikdasmen, 2024, 2025), a combination seldom found in either the international or the national literature reviewed. On this basis, the study is organized around the following three research questions (RQs).

RQ1: How is educational media transforming in response to the cognitive and behavioral formation of the algorithm generation's learning?

RQ2: What learning-adaptation strategies concerning the teacher's role, learners' AI literacy, and curriculum reorientation are needed for this transformation to move toward the augmentation and redefinition of learning rather than its inversion?

RQ3: What challenges and risks accompany this transformation, and how can a human-centered approach to AI integration mitigate them?

These three questions are addressed through the conceptual framework developed in Section 3 and the critical-comparative literature synthesis presented in Section 4.

II. RESEARCH METODE

A. Study Design

This study adopts a qualitative approach using a systematic-integrative library-research design. Following the typology of literature reviews proposed by Snyder (2019), a purely systematic review is best suited to studies with a narrowly defined purpose that permits quantitative aggregation of evidence (e.g., meta-analysis), whereas an integrative review is more appropriate when the aim is to critique and synthesize literature across traditions in order to generate a new model or theoretical framework. Because the present study aims both to synthesize understanding across sources and to construct a conceptual framework that positions the "algorithm generation" construct (see Section 3), it adopts a hybrid design: the identification, screening, and eligibility-assessment procedures

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follow PRISMA 2020 logic (Page et al., 2021) to ensure that the literature search and selection process is transparent and traceable, while the analysis and synthesis stages proceed through the integrative-thematic approach recommended by Snyder (2019) rather than through statistical aggregation.

B. Data Sources and Search Strategy

Data sources comprised nationally and internationally indexed journal articles, books, and official policy documents issued by institutions such as UNESCO and Indonesia's Ministry of Primary and Secondary Education. The literature search was conducted using the academic databases and search engines Scopus, Google Scholar, ScienceDirect, SpringerLink, ERIC, and arXiv. The search strategy combined Indonesian- and English-language keywords through Boolean operators, for example: "artificial intelligence in education") AND "adaptive learning" OR "personalized learning") AND ("algorithm-mediated learning" OR "digital natives"). The search was focused on publications from 2019 to 2025 in order to capture the latest developments in generative artificial intelligence, without disregarding earlier conceptual references (e.g., Prensky, 2001; Bennett et al., 2008) that serve as the study's theoretical-historical foundation.

C. Inclusion and Exclusion Criteria

The inclusion criteria were: (a) indexed, peer-reviewed journal articles or books, published in Indonesian or English; (b) official policy documents issued by credible governmental bodies or international organizations; (c) publication between 2019 and 2025, or foundational conceptual references that remain theoretically relevant; and (d) substantive engagement with artificial intelligence in education, the transformation of learning media, or the cognitive-behavioral characteristics of digital-native generations. The exclusion criteria were: (a) news articles, popular opinion pieces, or non-academic blog posts; (b) publications lacking a clear peer-review process or verifiable academic credibility; (c) findings duplicated in other, more recent and more comprehensive studies; and (d) sources with no substantive relevance to the study's theme despite appearing in the initial search results.

D. Data Selection Procedure

The data-selection procedure followed the four stages recommended by PRISMA 2020 (Page et al., 2021): identification, screening, eligibility assessment, and inclusion (see Figure 1). At the identification stage, the database search yielded 182 records, supplemented by 4 policy documents obtained from other sources, for a total of 186 records. After 34 duplicates were removed, 152 records were screened by title and abstract; 92 of these were excluded for lacking relevance to the theme, timeframe, or document type, leaving 60 articles for full-text eligibility assessment. At this stage, 38 articles were excluded for insufficient substantive engagement with educational media transformation or artificial intelligence (16), overlap with other, more recent and comprehensive studies (12), or failure to meet academic credibility standards (10), leaving 22 sources for synthesis in this conceptual-integrative study.

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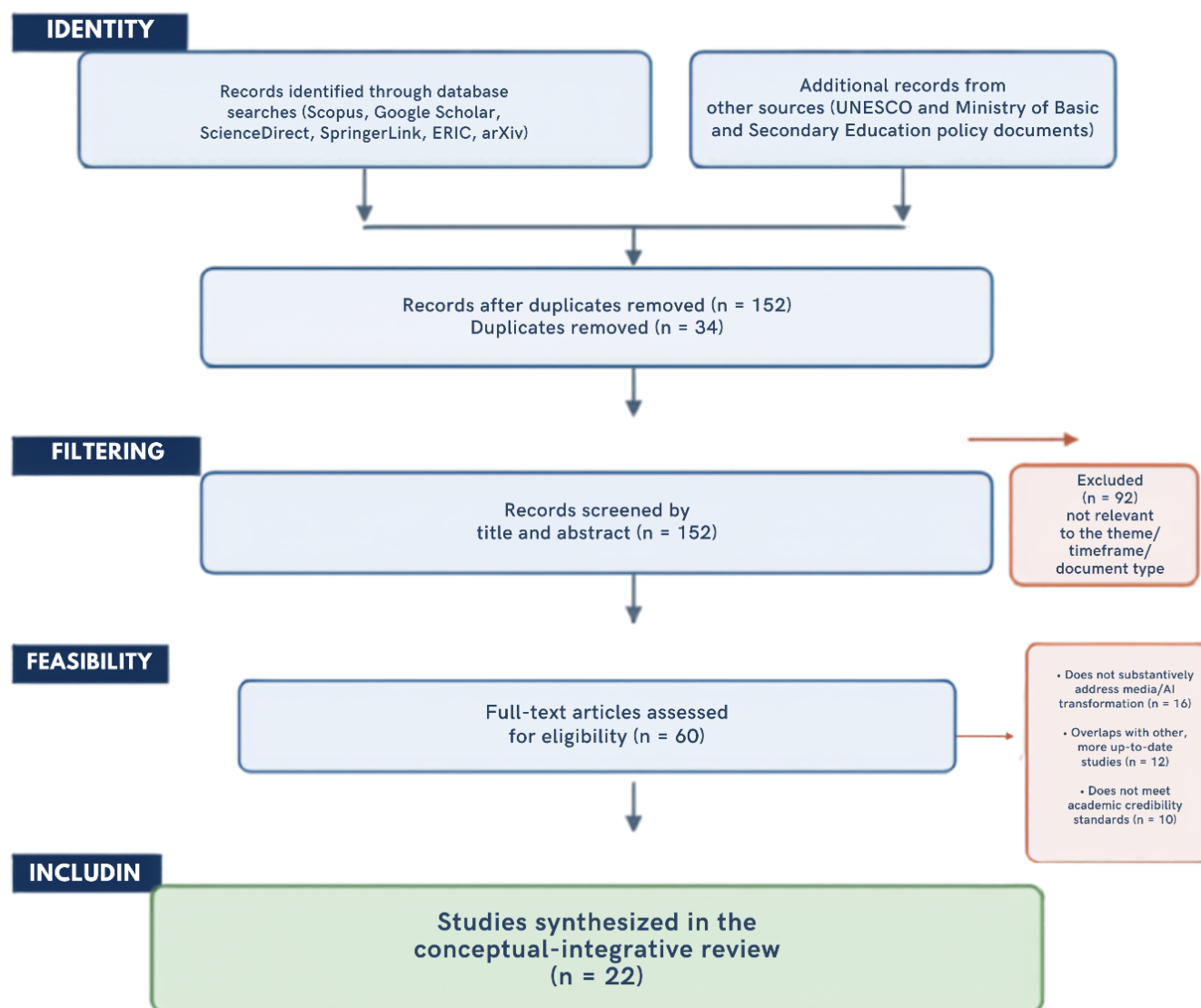


Figure 1. PRISMA flow diagram of the identification, screening, eligibility, and inclusion process

E. Data Analysis Technique

Data analysis was conducted through content analysis combined with integrative-thematic synthesis. The process comprised data reduction, categorization into major themes encompassing the dimensions of the algorithm-generation construct, the transformation of educational media, the AI-based digital ecosystem, learning-adaptation strategies, and their accompanying challenges and the presentation of findings as a critical-comparative narrative rather than a purely descriptive one. For each theme, relevant sources were explicitly compared according to context, method, and strength of evidence (e.g., large-scale systematic reviews versus single case studies), as presented in the synthesis table (Table 1) and the discussion in Section 4. The results of this thematic categorization were then abstracted into the conceptual framework presented in Section 3.

F. Methodological Limitations

Several methodological limitations must be acknowledged candidly. First, as a qualitative literature review, this study does not perform a statistical aggregation of effect sizes in the manner of a meta-analysis; the conclusions drawn are therefore conceptual rather than quantitative generalizations. Second, the screening and eligibility-assessment procedures were carried out by a single researcher without an inter-rater checking process, a limitation common to student-conducted literature reviews that should be addressed in future research. Third, and most importantly, “algorithm generation” is positioned in this study as a heuristic-analytic construct derived from conceptual synthesis rather than as an empirically validated psychometric construct; such validation for

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instance, through instrument development and psychometric testing constitutes a separate quantitative research agenda that lies beyond the scope of the present study (see Sections 3.2 and 5).

III. CONCEPTUAL FRAMEWORK: POSITIONING “ALGORITHM GENERATION” AS A CONSTRUCT

A. From “Digital Natives” to “Algorithm Generation”: A Conceptual Genealogy

Prensky (2001) was among the first scholars to state explicitly that today’s learners undergo a fundamental change in how they think and process information as a result of growing up amid digital technology from an early age. The term “digital natives” that he introduced became an important reference point for understanding the learning-style gap between learners and educators who came of age before digitalization became widespread. Seven years later, however, Bennett et al. (2008) conducted a critical review of the evidence underpinning the term and concluded that claims about digital generations are frequently overstated and insufficiently supported by empirical evidence, resembling an academic “moral panic” more than a theoretically well-established finding. They recommended a more measured, evidence-based approach to studying digital generations and their implications for education.

Bennett et al.’s (2008) critique serves as an important methodological warning for this study: any new generation-technology construct risks repeating the same error unless it is grounded in more specific, testable evidence. Rather than simply rebranding “digital natives” as “algorithm generation,” this study therefore grounds the construct in a more specific, empirically studied mechanism namely, the curation and personalization of content by digital-platform algorithms. Brady et al. (2023) show that algorithms on digital platforms tend to amplify the spread of emotionally charged, status-related, or morally inflected content, because such content is most effective at sustaining user attention not because it is accurate or useful. Bakshy et al. (2015), through a quantitative analysis of more than ten million Facebook users, provide further evidence that algorithmic ranking does reduce users’ exposure to ideologically diverse content, although and this matters for conceptual caution individual choice proved to be an even stronger constraining factor than the algorithm itself. In other words, “algorithm generation” must be understood as the product of an interaction between algorithmic design and user agency, rather than as technological determinism alone.

Building on this genealogy, the present study defines the algorithm generation as the cohort of learners whose thinking patterns, preferences, and learning habits are significantly shaped by sustained exposure to automated recommendation and content-curation systems, without assuming that this formation is uniform, deterministic, or independent of individual learner agency.

B. Construct Dimensions and Epistemic Status

Drawing on a synthesis of the reviewed literature, the algorithm-generation construct in this study is organized into three interrelated dimensions. The cognitive dimension encompasses a preference for concise, visual content and an attention span accustomed to rapid stimulus switching, as reflected in the way algorithms prioritize content that sustains instant engagement (Brady et al., 2023). The behavioral dimension encompasses an expectation of personalization and instant feedback, consistent with the broader shift toward adaptive learning systems powered by generative artificial intelligence (Khalifeh et al., 2026). The dispositional dimension encompasses a tendency toward information homophily the tendency to select and trust information that aligns with prior preferences as evidenced by patterns of restricted exposure to cross-cutting content (Bakshy et al., 2015).

It is important to emphasize that these three dimensions are constructed as a heuristic-analytic device for conceptual analysis within this literature review, not as a psychometric construct that has undergone empirical validation (e.g., factor analysis or instrument reliability-validity testing). This stance is consistent with the epistemic caution recommended by Bennett et al. (2008) in studying generation-technology constructs: the algorithm generation is used here as an analytic lens for understanding the new demands placed on educational-media design, not as a diagnostic or predictive category for any particular learner. Psychometric validation of this construct for example, through scale development and testing on the Indonesian learner population constitutes a further quantitative research agenda proposed in Section 5.

C. Conceptual Framework of the Study

The three dimensions of the algorithm-generation construct are positioned as the conceptual link between the algorithmic digital ecosystem and the need for educational-media transformation, as summarized in Figure 2. In this framework, the algorithmic digital ecosystem (Brady et al., 2023; Bakshy et al., 2015) shapes the algorithm generation at the cognitive, behavioral, and dispositional levels. This formation, in turn, demands that educational media transform from a static-linear model toward an adaptive, personalized, data-driven model (Zawacki-Richter et al., 2019; Khalifeh et al., 2026). This direction of transformation, however, is neither linear nor automatically positive: drawing on the ISAR framework proposed by Bauer et al. (2025), the application of artificial intelligence in educational media can move toward inversion (diminishing cognitive engagement), substitution (replacing old methods with functionally equivalent ones), augmentation (supporting existing learning processes), or redefinition (enabling new, deeper learning experiences).

Which ISAR position is ultimately reached, within this study’s framework, is moderated by two sets of factors. The first is the adequacy of learning-adaptation strategies at the level of teachers, learners, and curriculum (Rahmah, 2020; Casal-Otero et al., 2023; Kemendikdasmen, 2025). The second is the design orientation of the artificial intelligence itself specifically, the extent to which its

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implementation is human-centered, critical, and ethical (Miao & Holmes, 2023). When adaptation strategies are adequately implemented and the design orientation is human-centered, the transformation of educational media tends toward augmentation and redefinition, culminating in deeper and more contextual learning. Conversely, when these two conditions are not met, transformation risks becoming trapped in shallow inversion or substitution, culminating in access gaps, algorithmic bias, and the erosion of critical-thinking ability (Holstein & Doroudi, 2021).

This conceptual framework responds to the need identified by Mustafa et al. (2024) for a more comprehensive perspective capable of synthesizing AIED evidence that has thus far been scattered across isolated traditions and subtopics. It simultaneously serves as the analytic framework used to structure the critical-comparative synthesis presented in Section 4.

Conceptual Framework: The Position of the “Algorithm Generation” as a Linking Construct

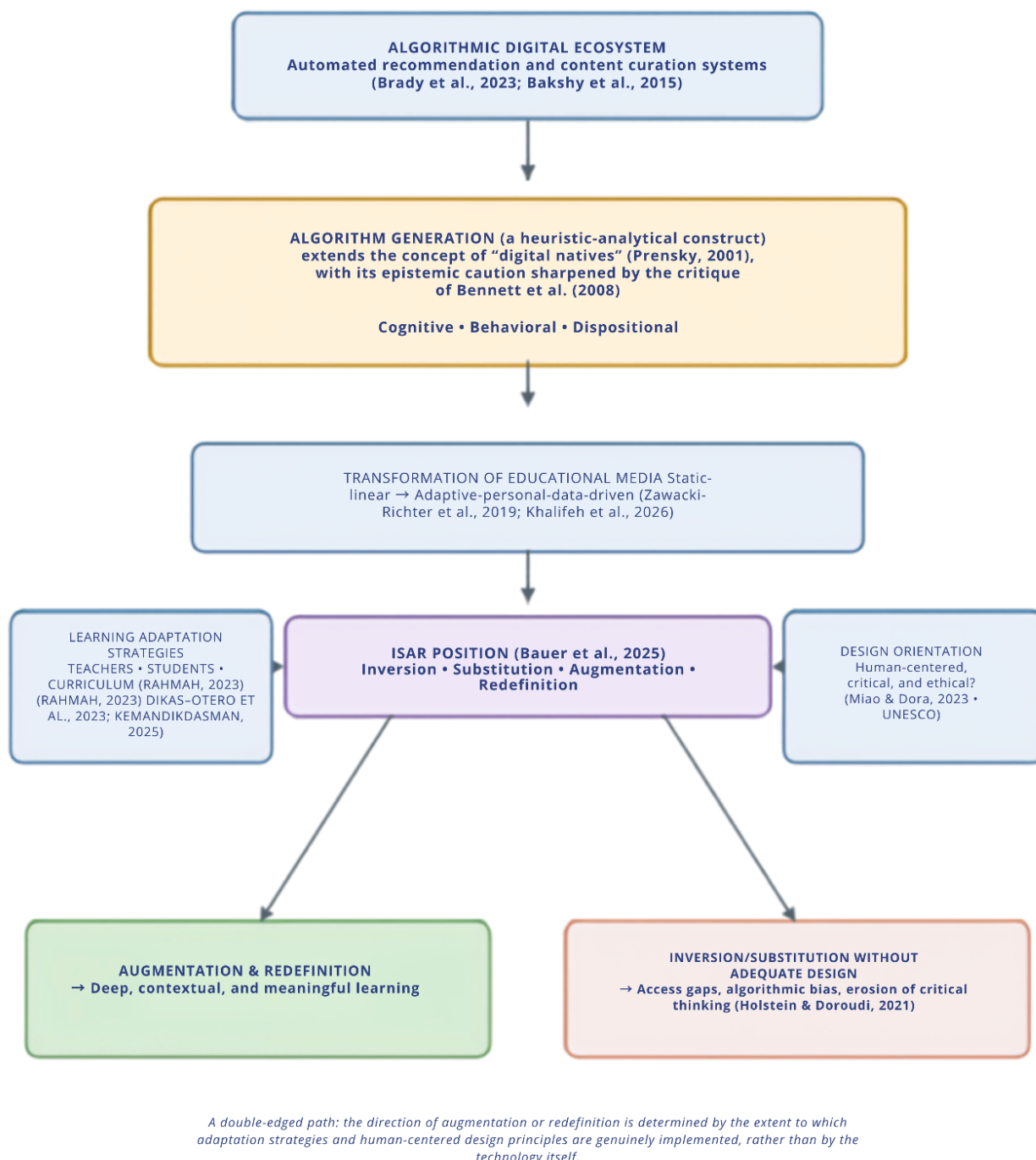


Figure 2. Conceptual framework positioning the algorithm generation as the construct linking the algorithmic digital ecosystem and the transformation of educational media.

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IV. RESULTS AND DISCUSSION

This section presents a critical-comparative synthesis of the 22 sources included in this study, organized to address the three research questions posed in Section 1. Table 1 summarizes the key sources underlying the synthesis, including their method, primary focus, key findings, and relevance to this study. Rather than presenting each source's findings sequentially and descriptively, the discussion below deliberately compares these sources against one another highlighting points of convergence, points of tension, contextual differences, and methodological strength in line with recommendations for literature reviews that aim to produce conceptual contributions rather than merely a descriptive summary (Snyder, 2019).

Table 4.1 Synthesis of Key Literature

No.	Author, Year & Method	Primary Focus	Key Findings	Relevance to This Study
1	Prensky (2001) conceptual	Characteristics of “digital natives”	Digital-native learners think and process information differently from previous generations.	Historical starting point for the generation-technology construct.
2	Bennett et al. (2008) critical review	Evaluation of “digital natives” evidence	Claims about digital generations often outrun empirical evidence; resemble an academic “moral panic.”	Basis for the epistemic caution in positioning algorithm generation as a heuristic construct.
3	Brady et al. (2023) cross-disciplinary conceptual synthesis	Algorithm-mediated social learning	Algorithms amplify emotional/moral content to sustain engagement, not accuracy.	Basis for the cognitive-behavioral dimension of the algorithm-generation construct.
4	Bakshy et al. (2015) large-scale quantitative (n > 10 million)	Exposure to ideological news on Facebook	Algorithmic ranking reduces $\approx$ 15% cross-cutting exposure; individual choice has a larger effect.	Quantitative evidence of algorithmic curation; replaces a less essential national news source.
5	Zawacki-Richter et al. (2019) systematic review (146 articles)	AI applications in higher education	Four categories of AI application; teacher voice minimally involved in their development.	Early map of AI applications in education (pre-generative AI).
6	Casal-Otero et al. (2023) systematic review	K-12 AI literacy	AI literacy divides into applied-technical approaches and theoretical frameworks.	Basis for AI literacy strategies for teachers and learners.
7	Bauer et al. (2025) conceptual synthesis (ISAR model)	Effects of AI on learning	Four effects: inversion, substitution, augmentation, redefinition.	Core analytic framework for this study's conceptual framework.
8	Holstein & Doroudi (2021) conceptual review	Equity and AI in education	Four perspectives on how AI risks widening existing educational inequities.	Basis for the inequity-risk argument in the Indonesian context.
9	Miao & Holmes (2023) UNESCO policy guidance	Generative AI in education	Human-centered approach; data protection; regulatory framework.	Basis for the human-centered design orientation in the conceptual framework.
10	Sailer & Homner (2020) meta-analysis	Effects of gamification on learning	Stable effects on learning achievement; more moderate effects on motivation and engagement.	Quantitative evidence reinforcing the adaptive-personalized media transformation.
11	Khalifeh et al. (2026) PRISMA systematic review (55 studies)	Redefining personalized learning in the AI era	Eight core components of AI-based personalized learning; complementary teacher-AI roles.	Methodological model for PRISMA; enriches the conceptual framework and discussion.
12	Mustafa et al. (2024) review of systematic reviews	AIED research landscape	AIED research is fragmented; a more comprehensive cross-thematic synthesis is needed.	Basis for the novelty argument and the need for an integrative framework.
13	Rahmah (2020) national conceptual study	Changing teacher roles in the digital era	Shift from instructor to digital facilitator.	Basis for the teacher-role adaptation argument in the Indonesian context.
14	Pratama & Sopandi (2023) national empirical study	Interactive platforms in secondary schools	Interactive platforms contribute to student participation and motivation.	National empirical evidence supporting media transformation.

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15	Kemendikdasmen (2024, 2025) policy documents	Deep learning and the Kurikulum Merdeka	Reinforcement of holistic conceptual understanding, critical thinking, and meaningful learning.	Basis for the relevance of Indonesian curriculum policy.
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A. Educational Media Transformation: Points of Convergence and Tension Across Contexts

The clearest point of convergence among the sources reviewed is agreement that educational media is shifting from a static, one-way model toward an adaptive, personalized one. Zawacki-Richter et al. (2019), through a systematic review of 146 higher-education research articles, identify four categories of AI application learner profiling and behavior prediction, automated assessment, adaptive systems, and intelligent tutoring systems. This review is a mapping, descriptive-categorical exercise, reflecting the state of the field prior to the widespread adoption of generative artificial intelligence. A far more recent review by Khalifeh et al. (2026), which explicitly updates a similar systematic review spanning 2019 to 2025, shows that the field has moved considerably further: personalization is now understood as a sociotechnical system comprising eight core components ranging from learner profiles and content models to adaptive engines and evaluation governance and is characterized by teacher and AI roles that complement rather than replace one another. Comparing these two reviews reveals an important shift: from merely mapping technological applications (2019) to understanding personalization as a more complex and structured system (2026), consistent with the growing prominence of generative artificial intelligence in recent years. Van Schoors et al. (2021), who examined twenty-five years of research on digital personalized learning at the primary and secondary levels, add an important historical perspective: the conceptual and methodological trends of research in this field continue to shift, meaning that findings at any given point in time should be read as a temporary snapshot rather than a final conclusion.

A more compelling tension emerges when these international findings are set against studies conducted in the Indonesian context. Mustaghfiroh et al. (2025) and Pratama and Sopandi (2023) both examine the transformation of learning media through the use of artificial intelligence and interactive platforms in secondary schools, yet both are case studies or observations of limited scale, in marked contrast to the scope of international systematic reviews that examine dozens or even hundreds of studies. This disparity in the scale of evidence warrants interpretive caution: a transformation that appears already “well-established” in the international literature has not necessarily been internalized evenly within Indonesian educational practice, and generalizations across contexts should therefore be made with care. On the other hand, the claim that interactive media increases learning participation and motivation which appears consistently in both Indonesian and international studies receives stronger support from the meta-analysis by Sailer and Homner (2020), who found stable effects of gamification on learning achievement but more moderate effects on student motivation and engagement. This “stable yet moderate” nuance matters: it corrects a tendency in some descriptive studies to conclude, overly optimistically, that interactive media is beneficial without distinguishing which type of learning outcome is actually affected.

B. The Algorithm Generation in the Classroom: Convergence and the Limits of Evidence

As explained in Section 3, the algorithm-generation construct is built on the convergence between Brady et al.’s (2023) findings on algorithms that optimize for emotional engagement and Bakshy et al.’s (2015) quantitative findings on the effect of restricted exposure to diverse content. These two sources reinforce one another at the level of mechanism algorithms do indeed optimize for attention rather than accuracy or diversity but diverge at the level of methodology and context: Brady et al. (2023) offer a cross-disciplinary conceptual synthesis spanning cognitive and social science, whereas Bakshy et al. (2015) present a large-scale observational study confined to a single platform (Facebook) and the context of political content in the United States. Generalizing Bakshy et al.’s findings to the domain of education and the Indonesian context should therefore be treated as an analogy of mechanism rather than as direct evidence.

A critical point that deserves emphasis and one frequently overlooked in popular narratives about the “algorithm generation” is Bakshy et al.’s (2015) finding that individual choice exerts a larger constraining effect than the ranking algorithm itself. This finding challenges deterministic narratives that place the algorithm as the sole cause of young people’s narrowing worldview, and it aligns with Bennett et al.’s (2008) epistemic warning against overstating claims about technological generations beyond the available evidence. The implication for educational media is twofold: educators cannot attribute learners’ narrowing perspectives entirely to “the algorithm,” yet neither can they rely on learner agency alone without deliberately redesigning educational media to promote exposure to diverse perspectives.

C. The Digital Ecosystem and the ISAR Framework: Comparing Analytic Lenses

The three analytic frameworks examined in this study Holmes et al.’s (2019) call for a wholesale rethinking of curriculum, Bauer et al.’s (2025) ISAR framework, and UNESCO’s human-centered guidance (Miao & Holmes, 2023) complement one another but operate at different levels. Holmes et al. (2019) operate at the most macro and prescriptive level, calling for curriculum rethinking without providing analytic categories that could be used to assess the quality of AI implementation in any particular case. Bauer et al.’s (2025) ISAR framework fills this gap by offering four more precise and operationalizable categories (inversion, substitution,

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augmentation, redefinition), though it focuses on the level of the teaching-learning process rather than on policy or regulation. UNESCO's guidance (Miao & Holmes, 2023) complements both by supplying principles at the policy and regulatory level data protection, age-appropriateness, and a regulatory framework that keeps pace with technological development.

Combining these three lenses matters precisely because none is sufficient on its own: the ISAR framework, without UNESCO's human-centered principles, risks becoming a value-neutral technical evaluation tool, whereas Holmes et al.'s (2019) call to "rethink curriculum," without the precision of the ISAR categories, risks remaining mere rhetoric. The conceptual framework in Section 3.3 of this study explicitly integrates all three positioning the ISAR outcome as a node moderated by both adaptation strategy and human-centered design orientation in response to the limitations each framework exhibits when used in isolation.

D. Learning-Adaptation Strategies: In Sync or Out of Step with Indonesian Policy?

Regarding the teacher's role, the argument for a shift from content deliverer to digital facilitator (Rahmah, 2020) aligns with the critique embedded in Zawacki-Richter et al.'s (2019) review, which questions the extent to which teacher voice has been involved in developing AI for education. Khalifeh et al.'s (2026) review, however, reveals a nuance worth weighing: in more mature AI-based personalization practice, teacher and AI-system roles are complementary, with teachers interpreting learner data, aligning system recommendations with curricular goals, and providing socio-emotional support that no algorithm can replace. This comparison suggests that the teacher's shift toward becoming a digital facilitator should not be read as the teacher becoming passive, but rather as a strengthening of the teacher's role in precisely those functions that cannot be automated.

Regarding learners, Casal-Otero et al.'s (2023) AI-literacy framework which distinguishes an applied-technical approach from a theoretical framework of AI literacy maps directly onto the cognitive and behavioral dimensions of the algorithm-generation construct discussed in Section 3.2: applied-technical literacy addresses the behavioral dimension (expectations of personalization and tool use), while theoretical literacy addresses the dispositional dimension (critical awareness of information homophily). Regarding curriculum, the deep-learning policy that reinforces the Kurikulum Merdeka (Kemendikdasmen, 2024, 2025) is structurally aligned with the augmentation-redefinition direction within the ISAR framework, as both emphasize holistic conceptual understanding and critical thinking. This alignment at the policy level, however, does not necessarily extend to the level of implementation: the Indonesian-context studies reviewed (Mustaghfiroh et al., 2025; Pratama & Sopandi, 2023) provide no evidence of the extent to which teachers are genuinely given room to participate in designing AI implementation within their own classrooms, as recommended by Zawacki-Richter et al. (2019). This gap between policy direction and implementation reality therefore stands as an important agenda for further empirical research.

E. Challenges and Risks: Weighing Optimism Against Caution

Holstein and Doroudi (2021) put forward four perspectives on why AI systems risk widening, rather than narrowing, educational inequities: sociotechnical design factors, training data that reflects historical inequality, factors intrinsic to machine-learning algorithms, and the complex interaction between automated and human decision-making. This argument is important for balancing the technological optimism implicit in some reviews of AI implementation (e.g., Khalifeh et al., 2026, which emphasizes effectiveness and scalability). This tension between technological optimism and critical caution does not mean that the two bodies of literature cancel each other out; rather, it confirms that the outcomes of AI implementation are contingent, exactly as the ISAR framework depicts: the potential for augmentation and the risk of inversion are equally real, and what determines which direction prevails is the quality of design and the context of implementation, not the technology itself.

UNESCO's guidance (Miao & Holmes, 2023) offers a normative solution to this risk through a human-centered approach, yet Mustafa et al.'s (2024) review warns that the fragmented AIED research landscape makes such normative principles difficult to translate consistently into practice, since each AIED subfield tends to develop its own norms and metrics. For the Indonesian context, disparities in digital infrastructure across regions (Holstein & Doroudi, 2021) are likely to interact with regulatory gaps that UNESCO itself acknowledges remain under development in most countries. The combination of these two gaps infrastructure and regulation indicates that the risk of eroded critical thinking arising from an algorithm generation accustomed to consuming information passively (Brady et al., 2023) cannot be addressed through intervention at the level of educational media alone, but requires aligned policy across infrastructure, regulation, and curriculum simultaneously.

V. CONCLUSION

This study demonstrates that the transformation of educational media in the age of the algorithm generation is not merely a cosmetic technological modernization, but a structural adaptation made necessary by the shift in learners' cognitive foundations and learning habits under the influence of the algorithmic digital ecosystem. In answer to RQ1, educational media has transformed from a static, one-way model toward an adaptive, personalized, data-driven model, underpinned by intelligent tutoring systems, adaptive learning content, and learning analytics although the depth of this transformation remains considerably more mature in the international literature than in documented practice in Indonesia.

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In answer to RQ2, this transformation demands comprehensive adaptation across three aspects: a shift in the teacher's role toward digital facilitation that is, in fact, strengthened in those functions that cannot be automated; enhanced AI literacy for both teachers and learners, spanning applied-technical as well as theoretical-critical dimensions; and curriculum reorientation toward deep and contextual learning, as reflected in the Kurikulum Merdeka policy. However, as the conceptual framework in Section 3 makes clear, this adaptation will culminate in the augmentation and redefinition of learning rather than its inversion only if these adaptation strategies are genuinely and adequately implemented, rather than merely codified in policy documents.

In answer to RQ3, the challenges accompanying this transformation digital access gaps, algorithmic bias, and the erosion of critical thinking are contingent rather than technologically inevitable, and can be mitigated through a human-centered, critical, and ethical approach to AI integration (Miao & Holmes, 2023) that is consistently translated into infrastructure, regulatory, and curriculum policy alike.

The novelty of this study positioning the algorithm generation as an explicit analytic construct, building an integrative conceptual framework, and connecting it to the Indonesian policy context is intended to serve as a reference point for AIED scholarship that, according to Mustafa et al. (2024), still requires a more comprehensive perspective. This study has limitations that must be candidly acknowledged: as a qualitative literature review, its findings are conceptual in nature, and the proposed algorithm-generation construct has not undergone psychometric validation. Further empirical, field-based research is greatly needed, both to test the validity of the algorithm-generation construct among the Indonesian learner population and to examine the direct implementation of AI-based adaptive educational media within Indonesian classroom contexts including in the domain of character and religious education such as Islamic Religious Education so as to complement the conceptual analysis offered in this study with more contextually grounded empirical evidence.

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