International Journal of Education Reports
How to Cite: Rogayan JR., D.V. & Nurprayoga LM, Y. (2026). Restricting AI Use Among Basic and Secondary Education Students: A Thematic Study of Policy Discourse. *International Journal of Education Reports*, *1*(1), 45-58.
Doi: https://doi.org/10.62503/ijer.1.1.45-58
Website Journal: https://journal.dealingspublishing.com/index.php/IJER/

RESEARCH

Restricting AI Use Among Basic and Secondary Education Students: A Thematic Study of Policy Discourse

Danilo V. Rogayan JR[1]*, and Yektie Nurprayoga LM [2]

Correspondence:

Danilo V. Rogayan, [1]Magsaysay State University Iba, Philippines, email: danrogayan@prmsu.edu.ph,

[2]Universitas Negeri Padang, Indonesia.

Received: 02/08/2026

Accepted: 11/08/2026

Abstract

The emergence of artificial intelligence (AI) in education has prompted varied policy responses worldwide. Indonesia joined this trend by issuing a Joint Decree of Seven Ministers (SKB) on 12 March 2026 restricting AI use among basic and secondary education students. This study analyzed the justificatory themes articulated by the Coordinating Minister for Human Development and Cultural Affairs (Menko PMK) and assessed their consistency with literature on cognitive debt, brain rot, and adolescent mental health. Using a descriptive qualitative design, the study combined thematic and framing analysis of a single primary data source, an official statement reconstructed from a news article, compared with academic sources published between 2021 and 2026. The analysis identified six themes: the restriction's scope, the cognitive-risk rationale, the differentiation between permitted and restricted AI use, cross-ministerial legitimacy, risk-mitigation framing, and adolescents digital-exposure context. The screen-time and mental-health arguments proved consistent with the literature, whereas the cognitive-debt argument oversimplified an ongoing debate over whether access restriction or design-based intervention more effectively addresses AI overreliance. To our knowledge, this is the first study to position a policymaker's official statement as the primary unit of analysis for an AI education-restriction policy in Indonesia, offering a meeting point between GenAI policy studies, cognitive-dependence research, adolescent mental-health literature, and Indonesian digital-literacy studies that have developed in isolation from one another. This study extends framing theory to educational technology policy beyond developed countries and underscores the need for technical guidelines emphasizing interaction design and differentiation across education levels, rather than uniform access restriction.

Keywords artificial intelligence in education; digital education policy; policy framing analysis; cognitive debt; children's digital literacy

INTRODUCTION

Since ChatGPT's public release in late 2022, large language model-based generative artificial intelligence (GenAI) has fundamentally reshaped education worldwide. It has enabled personalized learning and more efficient lesson preparation, yet it has also raised new concerns about academic integrity and the quality of students' thinking processes (Cotton et al., 2024; Fütterer et al., 2023; García-López & Trujillo-Liñán, 2025; Klarin et al., 2024; Kofinas et al., 2025; Yusuf et al., 2024). This transformation has unfolded far faster than most countries' regulatory capacity to respond (Hatz et al., 2025). The United Nations Educational, Scientific and Cultural Organization (UNESCO) issued its first global guidance on GenAI in education in 2023, precisely because most countries still lacked an adequate national regulatory framework at that time (Miao & Holmes, 2023). Several countries responded with varied approaches, ranging from temporary national restrictions grounded in data and child protection to outright bans across hundreds of school districts soon after ChatGPT's emergence (Farina & Lavazza, 2023; Hasanein & Sobaih, 2023; Roberts et al., 2023). This pattern shows that the tension between GenAI's potential benefits and risks for students is not merely an academic debate. It has become a real and urgent public-policy issue across jurisdictions.

Indonesia joined this global trend on 12 March 2026, when seven ministries and agencies signed a Joint Decree of Seven Ministers (SKB) on Guidelines for the Use and Teaching of Digital Technology and Artificial Intelligence across formal, non-formal, and informal education. The policy explicitly restricts basic and secondary education students' use of AI tools such as ChatGPT, while still permitting AI applications specifically designed for learning purposes, such as educational robotics simulations (Huang et al., 2023). The policymaker's justification rests on three terms currently prominent in global public discourse on the cognitive effects of digital technology: brain rot, cognitive debt, and children's cognitive decline. Public interest in this discourse has surged; Yousef et al. (2025) reported a 230% rise in the term brain rot's usage between 2023 and 2024, the year Oxford University Press named it Word of the Year. Each term has also become the subject of scholarly inquiry, yet the underlying evidence base remains narrow. The frequently cited cognitive-debt study, for example, drew on essay-writing sessions with only 54 participants, and just 18 completed its final session (Kosmyna et al., n.d.). Notably, a national-level policy that specifically targets basic and secondary education using these terms as justification remains a novel phenomenon. This novelty mirrors the thinness of the broader evidence base: a systematic review spanning Scopus and Web of Science identified only 30 studies worldwide on generative-AI use in K-12 settings, most concentrated on high school and preservice-teacher contexts (Alfarwan, 2025). How this reasoning was constructed, how it compares with available scientific evidence, and how the policymaker communicated it to the public therefore warrant systematic investigation.

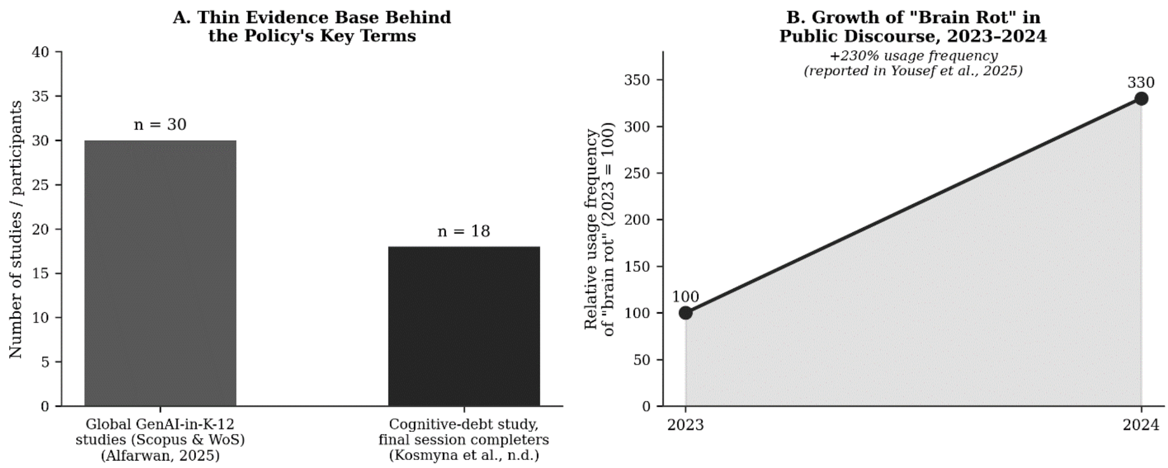

Figure 2. Empirical Context for The SKB Cognitive-Risk Justification

A number of studies emphasize that the negative effects of digital technology on children are not deterministic but are moderated by parental mediation and digital literacy levels. Ren & Zhu (2022) found that parenting style moderates the relationship between parental mediation and adolescents' internet use. Active mediation was associated with healthier internet-use patterns than purely restrictive mediation. Within the Indonesian context, several studies stress the importance of digital literacy as a foundation for responsible AI use (Mimoudi, 2025; Ng et al., 2021). Mustahar. AM et al. (2025) found that integrating digital literacy and artificial intelligence as a learning resource for senior high school students requires ethical awareness and data-security awareness, a digital-literacy gap between teachers and students that affects the quality of learning in the digital era. Senior high school and vocational school students tend to use AI differently, senior high school students lean toward analytical use, while vocational students favor practical applications. This finding suggests that a uniform restriction policy across all levels of basic and secondary education risks overlooking such variation in AI-use patterns. This body of Indonesian literature remains largely descriptive-exploratory, relying on library research or small-scale surveys. None of these studies has specifically examined national-level AI restriction policy or the discourse underlying it.

This study draws on two complementary theoretical foundations, cognitive offloading theory and framing theory, detailed in the Conceptual Framework section below. Four bodies of research have developed largely in isolation from one another: studies on GenAI education policy, which focus mainly on higher education and global institutional levels; experimental studies on cognitive dependence, which have yet to reach consensus and have not been tested against public policy discourse; studies on screen time and adolescent mental health, which draw primarily on data from developed countries; and Indonesian studies on digital literacy and parental mediation, which remain descriptive-exploratory and have not addressed national policy. The intersection of these four bodies of work, namely how arguments from the global cognitive and mental-health literature (brain rot, cognitive debt) are adopted, simplified, and communicated by policymakers in formulating AI restrictions for basic and secondary education students in Indonesia, remains unaddressed in existing research. This gap is especially relevant given that the SKB was signed only recently, on 12 March 2026. Consequently, no academic study has yet evaluated its justificatory discourse. This study is positioned to fill that gap through a thematic analysis of the policymaker's official statement, using relevant scientific literature as a benchmark to assess the consistency between the policy's arguments and the available evidence. The research problem addressed in this study, therefore, is how the Coordinating Minister's justificatory discourse for the AI restriction, particularly its reliance on the cognitive-debt and brain-rot rationale, aligns with or diverges from the available scientific evidence, and how this reasoning was rhetorically framed for public communication.

Based on the gap outlined above, this study was formulated around three specific and measurable objectives. The first objective was to identify and classify the justificatory themes of the AI restriction policy as articulated by the Coordinating Minister in the official statement on the SKB signed on 12 March 2026, producing a thematic matrix covering every available segment of the primary data source. The second objective was to systematically compare these themes with 2021–2026 scientific literature on cognitive debt, brain rot, screen time, and adolescent executive function, in order to evaluate how consistent the policy's arguments are with available empirical evidence, producing a consistency assessment for each identified theme. The third objective was to identify the rhetorical framing patterns the policymaker used to communicate the restriction as a risk-mitigation measure rather than a ban, producing a description of the framing mechanisms observed in the data. All three objectives were achievable within the study's designated timeframe because the single primary data source had been publicly available since the SKB's signing date**,** leaving sufficient time to complete data collection, coding, and analysis within the study period**.** They also directly serve the academic need to document and evaluate Indonesia's first policy of this kind on AI in education.

CONCEPTUAL FRAMEWORK

This study integrates two theoretical lenses to examine the SKB's justificatory discourse: cognitive offloading theory and framing theory. Each lens addresses a distinct research objective, and together they form a two-track analytical framework linking the policy's substantive content to its rhetorical construction. Figure 1 depicts this framework.

The first track draws on cognitive offloading theory (Risko & Gilbert, 2016; Sparrow et al., 2011), which explains how individuals delegate cognitive tasks to external tools rather than performing them internally. This framework anchors the evaluation of the policymaker's central claims, brain rot, cognitive debt, and children's cognitive decline, against the empirical literature on AI-assisted learning. Within this track, the policy's substantive argument is treated as a testable proposition: does offloading writing or reasoning tasks to generative AI produce the cognitive costs the policymaker describes, and does the available evidence support that claim at the scale implied by a national restriction?

The second track applies Entman (1993) framing theory, which identifies four functions performed by any policy communication: defining the problem, diagnosing its cause, rendering a moral judgment, and prescribing a remedy. Applied to the Coordinating Minister's official statement, this track examines how brain rot and cognitive debt were defined as risks (problem definition), how AI use was identified as their cause (causal attribution), how child protection was invoked to justify intervention (moral judgment), and how conditional restriction rather than an outright ban was proposed as the solution (remedy). This is illustrated by the "empowering, not endangering" framing device.

These two tracks converge on a single analytical question: how consistent is the substantive content of the policy's cognitive-risk argument with the framing used to communicate it? As shown in Figure 1, the SKB's official statement serves as the primary data source, feeding into parallel thematic and framing analyses. Thematic analysis, structured by cognitive offloading theory, produces a consistency assessment against the 2021–2026 scientific literature. Framing analysis, structured by Entman's four functions, produces a description of the rhetorical mechanisms used to communicate the restriction as protective rather than prohibitive. The two outputs are then synthesized to evaluate whether the policy's public justification aligns with, oversimplifies, or diverges from the underlying evidence base. This synthesis informs the theoretical, practical, and policy implications discussed in the final section.

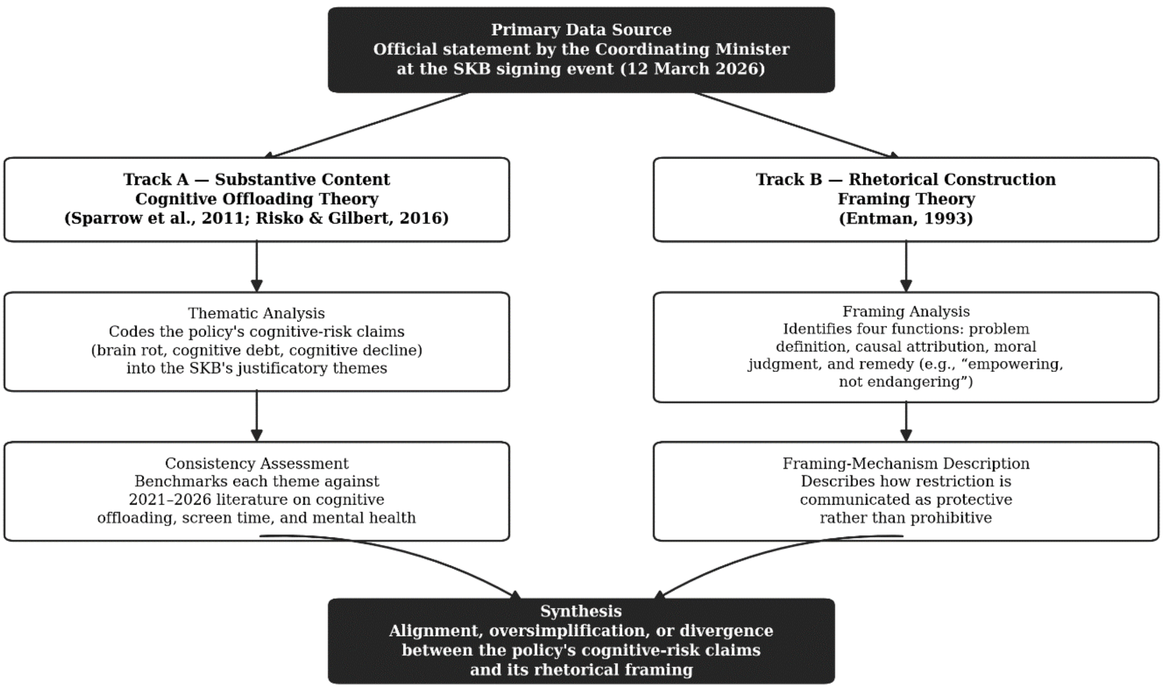

Figure 1. Conceptual Framework Integrating Cognitive Offloading and Framing Theory

RESEARCH METHODS

This study employed a descriptive qualitative design, using document and discourse analysis of a single primary data source, an official policy statement (Izadi et al., 2023). This design was chosen because of the nature of the research object itself: how a single policy actor, acting in an official capacity as Coordinating Minister, constructed and communicated the justification for restricting students' AI use through the SKB signed on 12 March 2026. Thematic and framing analysis were combined because they complement one another: thematic analysis identifies the substantive categories within the policy argument, while framing analysis dissects how that argument was rhetorically packaged for the public.
This study does not involve a physical research site, as its unit of analysis is a document-based, virtual data source: a news article reconstructing the Coordinating Minister's official statement at the SKB signing event, held on 12 March 2026. The "site" of this research is therefore textual and discursive rather than geographic, consistent with the document and discourse analysis design adopted in this study.
This study defined its unit of analysis as the corpus of official statements made by a key informant during a single public communication event. The informant serving as the data source was the Coordinating Minister. This informant was selected through purposive sampling, based on the following inclusion criteria. The statement had to originate from the official who served as lead coordinator of the SKB, be delivered at the official signing event, and be published by a traceable news source. The exclusion criteria ruled out statements from the six other signing ministries or agencies, since this study specifically targets the justificatory discourse articulated by the policy coordinator rather than the seven ministries' collective consensus. Statements from those other sources could form a separate line of future research. Because this study follows qualitative logic, data adequacy was assessed using the principle of information power rather than statistical power. Given the study's narrow and specific aim (analyzing the justificatory discourse of a single policy at a single event), its predetermined theoretical framework (cognitive offloading and framing), and its focused analytic strategy, one information-rich data source was deemed sufficient to meet the research objectives. This choice nonetheless limits the generalizability of the findings, as discussed in the limitations section.
The primary research instrument was the researcher (human as instrument), supported by a thematic coding matrix. This matrix was developed from the theoretical frameworks of cognitive offloading (Sparrow et al., 2011) and framing theory (Entman, 1993), as well as from categories emerging in the literature review on cognitive debt, brain rot, and screen time discussed in the introduction.

Data Collection
Data collection comprised the following three initial steps, while subsequent steps addressed data analysis. The first step involved locating and downloading the reconstructed interview transcript that served as the research material. The second step cross-checked the transcript's content against the source news article, confirming that the direct quotations matched the statements published in the original source. The third step segmented the data into question-and-answer units, explicitly marking each segment as either a direct quotation or a narrative summary. The fourth step applied open coding, assigning preliminary codes to each segment without predetermined categories, to capture meaning emerging inductively from the data. The fifth step developed themes through constant comparison, comparing codes across segments to identify patterns and group them into broader themes. The sixth step matched the inductively coded themes against the deductive coding matrix derived from the theoretical framework, identifying both convergence and divergence between data and theory. The seventh step conducted framing analysis, examining how each theme was communicated through word choice, problem definition, causal attribution, moral judgment, and remedy recommendation. The eighth step involved peer debriefing: discussing the coding results and themes with fellow researchers to test the plausibility of the interpretation. The ninth step produced the final thematic matrix, presenting themes, categories, representative quotations, and data type, as shown in the results section. These nine steps are summarized in Table 1.

Table 1. Nine-Step Data Collection Procedure

Step	Stage	Activity
1	Data location and retrieval	Located and downloaded the reconstructed interview transcript serving as the research material
2	Source verification	Cross-checked the transcript against the source news article to confirm that direct quotations matched the original statements
3	Data segmentation	Segmented the data into question-and-answer units, marking each segment as either a direct quotation or a narrative summary
4	Open coding	Assigned preliminary codes to each segment without predetermined categories, capturing meaning emerging inductively from the data
5	Theme development	Developed themes through constant comparison, comparing codes across segments to identify patterns and group them into broader themes
6	Deductive matching	Matched inductively coded themes against the deductive coding matrix derived from the theoretical framework, identifying convergence and divergence between data and theory
7	Framing analysis	Examined how each theme was communicated through word choice, problem definition, causal attribution, moral judgment, and remedy recommendation
8	Peer debriefing	Discussed coding results and themes with fellow researchers to test the plausibility of the interpretation
9	Final matrix production	Produced the final thematic matrix, presenting themes, categories, representative quotations, and data type

Data Analysis

Data analysis combined thematic and framing analysis, conducted manually with the support of word-processing and spreadsheet software to document the coding process transparently. Thematic analysis was chosen for its suitability in identifying patterns of meaning within a limited body of textual data, without requiring distributional assumptions. Framing analysis was chosen because the second and third research objectives specifically target how the policymaker communicated the argument, not merely its content. Because the data consisted of fully published text with no truncated or unavailable sections, there was no missing data in the statistical sense requiring imputation.

Data Validation

Data validity in this study was addressed through several strategies. First, source triangulation was partially achieved by cross-checking the reconstructed transcript against the original news article to confirm the accuracy of direct quotations (step two of the data collection process). Second, peer debriefing was conducted, in which the coding results and emerging themes were discussed with fellow researchers to test the plausibility of the interpretation and reduce individual researcher bias. Third, an audit trail was maintained through the coding matrix, which documents each stage from open coding to the final thematic matrix, allowing the analytical process to be traced and replicated. These strategies correspond to the credibility and dependability criteria commonly used to establish trustworthiness in qualitative research. The study's reliance on a single primary data source nonetheless limits the extent to which triangulation across multiple independent sources could be achieved, a limitation discussed further in the Discussion section.

RESULTS AND DISCUSSION

Research Results

The thematic findings are presented in the order of the research objectives, following the reconstructed interview's flow: from the policy's scope, its underlying arguments, the boundary between prohibited and permitted use, the institutional actors involved, the informant's policy framing, to the supporting context of children's and adolescents' digital exposure. The first finding shows that the policy explicitly targets basic and secondary education, defining its restricted object as "AI" and illustrating it through direct question-and-answer interaction with services such as ChatGPT. The informant stated: "For example, basic and secondary education (students) are not permitted to use AI, such as asking ChatGPT and so on." It should be noted that the term "AI" was not given a more detailed operational definition in the available data. This category appears to refer to a pattern of use, namely requesting direct answers, rather than to a specific type of technology.

Regarding the rationale for the restriction, the informant raised three interrelated terms as the basis for the argument, centered on the potential decline in cognitive function from excessive AI exposure: "This is to avoid brain rot, to avoid cognitive debt, and the reduction of children's cognition." These three terms were presented without reference to specific data or scientific studies in the available statement, which is an important caveat for interpreting the results proportionately. The statement functions as a policy argument rather than a claim substantiated by direct empirical evidence from the informant within this dataset. Nonetheless, the data also show that the policy does not amount to a blanket ban on digital technology and AI in education. The informant distinguished between restricted AI and AI designed specifically for learning needs, stating: "We need to use that technology to support education, for instance, robotics simulations for basic education can use AI, but it must be designed for educational purposes." The example given, robotics simulation, indicates that the distinguishing criterion the informant emphasized was the application's design purpose, namely being built for learning, rather than the type of AI technology itself.

Institutionally, the SKB was signed by seven ministries and agencies: the Ministry of Higher Education, Science, and Technology; the Ministry of Home Affairs; the Ministry of Basic and Secondary Education; the Ministry of Religious Affairs; the Ministry of Communication and Digital Affairs; the Ministry of Women's Empowerment and Child Protection; and the National Population and Family Development Agency (BKKBN), under the coordination of the Coordinating Minister for Human Development and Cultural Affairs (Menko PMK), whose official statement at the signing event serves as this study's primary data source. This cross-sectoral scope, spanning education, home affairs, religious affairs, digital communication, women's and children's protection, and population and family affairs, indicates that the policy is positioned not merely as a technical education matter but also as a broader issue of child protection and digital governance (Ayalew et al., 2024). Consistent with this, the informant explicitly denied that the policy was intended to hinder children's technological development, framing it instead as a risk-mitigation measure: "This SKB does not obstruct. Rather, it regulates in order to mitigate risk on one hand, while digital technology and artificial intelligence, on the other hand, are meant to empower, not endanger, our children." This word choice echoes a deliberate phonetic pun in the original Indonesian statement between *memberdayakan* ("to empower") and *memperdayakan* ("to deceive or take advantage of," rendered here in translation as "endanger" to preserve the rhetorical contrast), which reflects a deliberate rhetorical framing effort to assert that the policy's purpose is protective rather than merely restrictive.

As background for the policy argument, the informant also cited data on high levels of digital exposure among Indonesian children and adolescents, linking it to rising mental-health disorders: "So screen time is over 7.5 hours, meaning green time (time spent outdoors or away from screens) is getting smaller. There are certainly many factors involved, but the rate of mental-health disorders among adolescents is high and keeps rising." In narrative form, not as a direct quotation, the informant also conveyed that underage social-media use can trigger mental-health disorders and that digital-technology addiction is one cause of the rise in mental-health disorders among minors. It should be noted that the figure of "over 7.5 hours" was presented without specifying the measurement method, period, or data source. This figure should therefore be treated as the informant's claim rather than as a statistic cross-verified within this study.

Consistent with the principle of reporting supporting and non-supporting findings equally, several aspects that remain unaddressed or unexplained in the available data must also be noted. These cannot serve as a basis for conclusions. No explanation was found regarding the monitoring,

sanctioning, or enforcement mechanisms at the school level. The term "AI" also lacked an explicit technical definition beyond the ChatGPT example, so the scope of other applications falling under this category cannot be determined from this data. The claims regarding brain rot, cognitive debt, and the 7.5-hour screen-time figure were not accompanied by any reference to data sources or studies in the informant's statement. The empirical basis for these claims therefore falls outside the scope of this study's data. The data also did not include the perspectives of other stakeholders, such as students, teachers, or parents (Famaye et al., 2024). The findings are therefore limited to a single informant's perspective from the policymaker's side. The absence of elaboration on these aspects does not imply that they are unimportant. Rather, it reflects the boundaries of the data source available for this study.
Taken together, these six themes indicate that the policymaker's justification operates on two levels simultaneously: a substantive level, grounded in cognitive and mental-health risk arguments, and a rhetorical level, in which restriction is deliberately framed as protective rather than prohibitive. The coexistence of a categorical restriction with a permitted-use exception for education-designed AI suggests that the policy's underlying logic is oriented toward use-pattern rather than technology-type, a distinction whose scientific adequacy is examined further in the following discussion. Each theme also carries a distinct evidentiary weight: the screen-time and mental-health themes rest on claims that are, in principle, verifiable against existing epidemiological literature, whereas the cognitive-debt and brain-rot themes rest on emerging and still-contested scientific constructs. This asymmetry in evidentiary maturity across themes is what the following discussion evaluates in detail.

Discussion

The policy's argument concerning brain rot and cognitive debt aligns with the general direction of the cognitive offloading literature, which is rooted in the classic finding that individuals tend to transfer cognitive load to external tools when such tools are available (Risko & Gilbert, 2016; Sparrow et al., 2011), and which has been updated by recent findings on the potential decline in neural connectivity resulting from reliance on AI assistants for writing tasks (Fleerackers et al., 2025; Kosmyna et al., n.d.). However, the policy appears to oversimplify a debate that is, in fact, far more nuanced within that literature. Buçinca et al. (2021) showed that overreliance on AI can be effectively mitigated through interface design, specifically cognitive forcing functions, without restricting access to the technology itself. Klingbeil et al. (2024) similarly found that the degree of dependence hinges on task context and user trust rather than on AI's mere presence. Fan et al. (2025), meanwhile, demonstrated that metacognitive laziness emerges depending on how and when AI is used during learning, rather than on AI use per se. Although drawn from a limited set of studies, these findings converge on a consistent pattern within the interface-design and human-AI interaction literature: overreliance is contingent on how AI is used, not merely on whether it is used at all. Consequently, the age based restriction adopted in the SKB actually conflicts with the main implication of the very literature it implicitly invokes, that design based interventions are better supported by evidence than categorical access restrictions, a pattern echoed in the school smartphone-ban literature, where categorical bans generally show weak or inconsistent effects on wellbeing outcomes (Böttger & Zierer, 2024; Campbell et al., 2024; Goodyear et al., 2025; Vanluydt et al., 2026). This finding extends our understanding of how contested scientific concepts can become oversimplified when translated into public policy discourse, a phenomenon rarely documented in prior AI education-policy literature, which has generally focused on institutional or higher-education levels (Hasanein & Sobaih, 2023).
In contrast, the policy's argument regarding digital exposure and adolescent mental health is generally consistent with well-established literature. The finding that high screen time is associated with adolescent mental-health disorders has been supported by a systematic review (Santos et al., 2023), a longitudinal review of attention-deficit/hyperactivity disorder (ADHD) symptoms (Thorell et al., 2024), and a rapid review of executive function (Maeneja et al., 2025). This consistency strengthens the scientific legitimacy of the policymaker's concern on this theme, even though the manner of presentation, particularly the 7.5-hour figure cited without specifying the measurement method, period, or data source, falls short of the methodological transparency typically found in the

comparison studies. This gap in methodological transparency between policy discourse and academic literature constitutes one of the study's contributions. The issue lies not in the substantive validity of the concern itself, but in how the supporting evidence was presented.

One finding that appears contradictory at first glance is the coexistence of firm restrictive rhetoric, avoiding brain rot and cognitive debt, with a government policy that simultaneously promotes coding and AI as elective subjects, from fifth grade through senior high school, starting in the 2025–2026 academic year. This tension can be explained through Entman (1993) framing framework, in which the policymaker appears to deliberately separate two distinct framing objects: "AI" as a cognitive threat on one hand, and "AI designed for education" as a means of empowerment on the other. This separation allows both narratives to coexist without appearing contradictory to the public. Further analysis of related policy documents indicates that this distinction may be operationalized in even greater detail through a tiered-zone framework, namely prohibited zones, restricted zones with rules, and recommended zones requiring reflection. Although this framework does not appear in this study's primary data, it is relevant for understanding that what looks like a rhetorical contradiction may in fact be translated into more detailed technical differentiation at the implementation level. This interpretation is theoretical, grounded in the framing framework applied, rather than a causal claim, given that the study's primary data did not directly reference this zoning scheme.

IMPLICATION

Theoretically, this study contributes to two areas. First, it extends the application of framing theory (Entman, 1993) to the domain of AI education-policy discourse in Indonesia, a context largely unexamined in prior technology-policy framing literature, which has focused predominantly on developed countries (Nguyen & Hekman, 2024; Ulnicane & Aden, 2023). Second, this study demonstrates that the concepts of cognitive offloading and cognitive debt, whose degree of generalizability remains debated at the academic level (Buçinca et al., 2021; Kosmyna et al., n.d.), have been translated into public policy discourse with far less nuance than in their originating literature. This phenomenon may be termed science-to-policy simplification and could serve as a conceptual framework for future research on how popular scientific terms are adopted into regulation. This theoretical contribution remains propositional and requires further testing across other policy cases, since this study analyzed only a single policy case.

Practical Implications

Practically, these findings carry concrete implications for policymakers and education practitioners. For policymakers, the gap identified between the design/context-based literature (Buçinca et al., 2021; Fan et al., 2025) and the age-category restriction suggests that the SKB's technical implementation guidelines should place greater emphasis on training teachers to design tasks that promote cognitive forcing, for example, requiring students to draft their initial reasoning before using AI to check their work, rather than simply banning access for a given age group (Nazaretsky et al., 2022), consistent with calls in the AI-literacy literature for structured, age-appropriate competency frameworks rather than blanket restriction (Casal-Otero et al., 2023; Chiu et al., 2024).

Policy/Government Implications

For government and policymakers, these findings imply that the SKB's technical implementation guidelines should be revised to emphasize interaction design and cognitive-forcing task requirements rather than uniform age-based access restriction. Guidance should also be differentiated between senior high school and vocational school contexts, as their AI-use patterns diverge and vocational schools may require technical guidance distinct from that of general schools (Antonietti et al., 2022), much as school-level implementation of restrictive and permissive device policies has been shown to vary considerably in design and rationale (Randhawa et al., 2025). Institutions implementing the SKB may also benefit from the kind of structured faculty-facing policy guidance documented in higher-education academic-integrity practice (Alsharefeen & Al Sayari, 2025). Finally, given the methodological gap identified in the informant's uncited screen-time figure, government communication teams should adopt a standard practice of citing verifiable data sources when presenting statistics to justify public policy, in order to sustain public trust and credibility before a public that is increasingly critical of data-based claims.

Indonesia's AI restriction policy for basic and secondary education students is built on cognitive and mental-health concerns with a legitimate scientific foundation. Yet it has been translated into a categorical restriction that is, in fact, poorly aligned with the main direction of the literature it implicitly invokes, literature that favors design- and context-based intervention over mere access restriction. This gap between the richness of scientific nuance and the simplicity of the policy narrative constitutes this study's core contribution, and it deserves central attention from both scholars studying AI education policy and policymakers designing technical guidelines for its implementation on the ground.

CONCLUSION

This study conducted a thematic analysis of the justificatory discourse behind the policy restricting AI use among basic and secondary education students, as articulated by the Coordinating Minister in the SKB, thereby addressing the three research objectives set out at the outset. For the first objective, the study identified six justificatory themes: the restriction's scope within basic and secondary education, the cognitive-risk-based argument, the differentiation of permitted AI use, cross-ministerial legitimacy, the policy's risk-mitigation framing, and the supporting context of digital-exposure and adolescent mental-health data. For the second objective, comparison with the 2021–2026 literature showed that the policy's arguments about screen time and adolescent mental health are generally consistent with available scientific evidence. In contrast, its arguments about cognitive debt and brain rot oversimplify an ongoing scientific debate, specifically, whether cognitive dependence on AI is more appropriately mitigated through access restriction or through interaction design and use-context. For the third objective, the framing analysis showed that the policy was deliberately communicated as a protective, rather than restrictive, measure, through the categorical separation between "AI" as a threat and "AI for education" as a tool of empowerment.

This study's principal contribution lies in filling the gap identified in the introduction. The previously unaddressed intersection of four bodies of literature that have developed separately, namely GenAI education-policy studies focused on global institutional and higher-education levels, experimental studies on cognitive dependence that have not reached consensus, screen-time and adolescent mental-health studies based on developed-country data, and Indonesian digital-literacy studies that have not yet addressed national policy. By analyzing the discourse of Indonesia's first national AI education policy explicitly targeting basic and secondary education, this study provides an empirical meeting point for these four bodies of literature. It also introduces a new lens for reading educational technology policy, one that examines not only the substantive validity of its arguments but also how those arguments are rhetorically framed for the public. This significance lies in the novelty of the research object itself. To the best of our knowledge, no prior academic study has positioned a policymaker's official statement as the primary unit of analysis for evaluating AI education-restriction policy in Indonesia.

Theoretically, this study shows that scientific concepts whose generalizability remains contested, such as cognitive debt, may be oversimplified when translated into public policy discourse, a pattern that enriches the application of framing theory to educational technology policy beyond developed countries. Practically, these findings direct policymakers' and schools' attention toward the need for technical guidelines that emphasize interaction design and differentiation across education levels, rather than uniform access restriction. This study's reliance on a single data source and a single informant nonetheless opens the way for future research that triangulates this discourse with the SKB's official text, statements from other ministries, and the firsthand experiences of students and teachers.

In a broader context, these findings reflect a challenge faced by many developing countries as they attempt to respond to a pace of AI development that far outstrips both available scientific evidence and existing regulatory capacity. Public policy must often be formulated amid scientific uncertainty, so an easily understood public narrative becomes a comprehensible shortcut, yet one that risks oversimplifying nuances that are, in fact, essential to the policy's own effectiveness. Indonesia's experience in formulating the SKB is therefore not merely a technical education matter. It also reflects how countries outside the centers of global technological innovation negotiate their position between protecting younger generations and keeping pace with digital transformation. Ultimately, this study affirms that good policy for Indonesian children in the age of artificial intelligence is defined not by the forcefulness of its restrictive rhetoric, but by how carefully it translates the complexity of scientific evidence into guidelines that can genuinely be implemented in the classroom.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the preparation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

REFERENCES

Alfarwan, A. (2025). Generative AI use in K-12 education: a systematic review. In *Frontiers in Education* (Vol. 10). Frontiers Media SA. https://doi.org/10.3389/feduc.2025.1647573

Alsharefeen, R., & Al Sayari, N. (2025). Examining academic integrity policy and practice in the era of AI: a case study of faculty perspectives. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1621743

Ayalew, Y. E., Verdoodt, V., & Lievens, E. (2024). General Comment No. 25 on Children’s Rights in Relation to the Digital Environment: Implications for Children’s Right to Privacy and Data Protection in Africa. *Human Rights Law Review*, *24*(3). https://doi.org/10.1093/hrlr/ngae018

Böttger, T., & Zierer, K. (2024). To Ban or Not to Ban? A Rapid Review on the Impact of Smartphone Bans in Schools on Social Well-Being and Academic Performance. In *Education Sciences* (Vol. 14, Number 8). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/educsci14080906

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-assisted Decision-making. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1). https://doi.org/10.1145/3449287

Campbell, M., Edwards, E. J., Pennell, D., Poed, S., Lister, V., Gillett-Swan, J., Kelly, A., Zec, D., & Nguyen, T. A. (2024). Evidence for and against banning mobile phones in schools: A scoping review. *Journal of Psychologists and Counsellors in Schools*, *34*(3), 242–265. https://doi.org/10.1177/20556365241270394

Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). AI literacy in K-12: a systematic literature review. In *International Journal of STEM Education* (Vol. 10, Number 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s40594-023-00418-7

Chiu, T. K. F., Ahmad, Z., Ismailov, M., & Sanusi, I. T. (2024). What are artificial intelligence literacy and competency? A comprehensive framework to support them. *Computers and Education Open*, *6*. https://doi.org/10.1016/j.caeo.2024.100171

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Entman, R. M. (1993). Framing: Toward Clarification of a Fractured Paradigm. *Journal of Communication*, *43*(4), 51–58. https://doi.org/10.1111/j.1460-2466.1993.tb01304.x

Famaye, T., Bailey, C. S., Adisa, I., & Irgens, G. A. (2024). "What Makes ChatGPT Dangerous is Also What Makes It Special": High-School Student Perspectives on the Integration or Ban of Artificial Intelligence in Educational Contexts. *International Journal of Technology in Education*, *7*(2), 174–199. https://doi.org/10.46328/ijte.651

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/https://doi.org/10.1111/bjet.13544

Farina, M., & Lavazza, A. (2023). ChatGPT in society: emerging issues. *Frontiers in Artificial Intelligence*, *6*. https://doi.org/10.3389/frai.2023.1130913

Fleerackers, A., Ratcliff, C. L., Wicke, R., King, A. J., & Jensen, J. D. (2025). Public understanding of preprints: How audiences make sense of unreviewed research in the news. *Public Understanding of Science*, *34*(2), 154–171. https://doi.org/10.1177/09636625241268881

Fütterer, T., Fischer, C., Alekseeva, A., Chen, X., Tate, T., Warschauer, M., & Gerjets, P. (2023). ChatGPT in education: global reactions to AI innovations. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-42227-6

García-López, I. M., & Trujillo-Liñán, L. (2025). Ethical and regulatory challenges of Generative AI in education: a systematic review. In *Frontiers in Education* (Vol. 10). Frontiers Media SA. https://doi.org/10.3389/feduc.2025.1565938

Goodyear, V. A., Randhawa, A., Adab, P., Al-Janabi, H., Fenton, S., Jones, K., Michail, M., Morrison, B., Patterson, P., Quinlan, J., Sitch, A., Twardochleb, R., Wade, M., & Pallan, M. (2025). School phone policies and their association with mental wellbeing, phone use, and social media use (SMART Schools): a cross-sectional observational study. *The Lancet Regional Health - Europe*, *51*. https://doi.org/10.1016/j.lanepe.2025.101211

Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and Consequences of ChatGPT Use in Higher Education: Key Stakeholder Perspectives. *European Journal of Investigation in Health, Psychology and Education*, *13*(11), 2599–2614. https://doi.org/10.3390/ejihpe13110181

Hatz, S., Dreksler, N., Wei, K., & Zhang, B. (2025). Local US officials' views on the impacts and governance of AI: Evidence from 2022 and 2023 survey waves. *PLOS ONE*, *20*(10 October). https://doi.org/10.1371/journal.pone.0332919

Huang, S., Lai, X., Li, Y., Wang, W., Zhao, X., Dai, X., Wang, H., & Wang, Y. (2023). Does parental media mediation make a difference for adolescents? Evidence from an empirical cohort study of parent-adolescent dyads. *Heliyon*, *9*(4). https://doi.org/10.1016/j.heliyon.2023.e14897

Izadi, R., Bahrami, M. A., Sarikhani, Y., & Bastani, P. (2023). Qualitative document analysis on Iranian contents and trends of population policies: Lessons learned and avenues for future. *Heliyon*, *9*(6). https://doi.org/10.1016/j.heliyon.2023.e17377

Klarin, J., Hoff, E., Larsson, A., & Daukantaitė, D. (2024). Adolescents' use and perceived usefulness of generative AI for schoolwork: exploring their relationships with executive functioning and academic achievement. *Frontiers in Artificial Intelligence*, *7*. https://doi.org/10.3389/frai.2024.1415782

Klingbeil, A., Grützner, C., & Schreck, P. (2024). Trust and reliance on AI — An experimental study on the extent and costs of overreliance on AI. *Computers in Human Behavior*, *160*. https://doi.org/10.1016/j.chb.2024.108352

Kofinas, A. K., Tsay, C. H. H., & Pike, D. (2025). The impact of generative AI on academic integrity of authentic assessments within a higher education context. *British Journal of Educational Technology*, *56*(6), 2522–2549. https://doi.org/10.1111/bjet.13585

Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X.-H., Beresnitzky, A. V., Braunstein, I., & Maes, P. (n.d.). *Your Brain on ChatGPT: Accumulation of Cognitive Debt when Using an AI Assistant for Essay Writing Task ⊿*.

Maeneja, R., Rato, J., & Ferreira, I. S. (2025). How Is the Digital Age Shaping Young Minds? A Rapid Systematic Review of Executive Functions in Children and Adolescents with Exposure to ICT. In *Children* (Vol. 12, Number 5). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/children12050555

Mimoudi, A. (2025). Generative AI to bridge the educational divide: Personalized learning and challenges. *Social Sciences and Humanities Open*, *12*. https://doi.org/10.1016/j.ssaho.2025.102140

Mustahar. AM, Muh. A., Haris, H., & Tenri Awaru, A. O. (2025). Integrasi Literasi Digital dan Kecerdasan Buatan sebagai Sumber Belajar bagi Siswa SMA. *Indo-MathEdu Intellectuals Journal*, *6*(7), 11306–11320. https://doi.org/10.54373/imeij.v6i7.4424

Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, *53*(4), 914–931. https://doi.org/10.1111/bjet.13232

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, *2*. https://doi.org/10.1016/j.caeai.2021.100041

Nguyen, D., & Hekman, E. (2024). The news framing of artificial intelligence: a critical exploration of how media discourses make sense of automation. *AI and Society*, *39*(2), 437–451. https://doi.org/10.1007/s00146-022-01511-1

Randhawa, A., Pallan, M., Twardochleb, R., Adab, P., Al-Janabi, H., Fenton, S., Jones, K., Michail, M., Patterson, P., Sitch, A., Wade, M., & Goodyear, V. A. (2025). Secondary school smartphone policies in England: a descriptive analysis of how schools rationalize, design, and implement restrictive and permissive phone policies. *Journal of Research on Technology in Education*, *57*(5), 1113–1132. https://doi.org/10.1080/15391523.2024.2363204

Ren, W., & Zhu, X. (2022). Parental Mediation and Adolescents' Internet Use: The Moderating Role of Parenting Style. *Journal of Youth and Adolescence*, *51*(8), 1483–1496. https://doi.org/10.1007/s10964-022-01600-w

Risko, E. F., & Gilbert, S. J. (2016). Cognitive Offloading. *Trends in Cognitive Sciences*, *20*(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002

Roberts, H., Babuta, A., Morley, J., Thomas, C., Taddeo, M., & Floridi, L. (2023). Artificial intelligence regulation in the United Kingdom: a path to good governance and global leadership? *Internet Policy Review*, *12*(2). https://doi.org/10.14763/2023.2.1709

Santos, R. M. S., Mendes, C. G., Sen Bressani, G. Y., de Alcantara Ventura, S., de Almeida Nogueira, Y. J., de Miranda, D. M., & Romano-Silva, M. A. (2023). The associations between screen time and mental health in adolescents: a systematic review. *BMC Psychology*, *11*(1). https://doi.org/10.1186/s40359-023-01166-7

Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google Effects on Memory: Cognitive Consequences of Having Information at Our Fingertips. *Science*, *333*(6043), 776–778. https://doi.org/10.1126/science.1207745

Thorell, L. B., Burén, J., Ström Wiman, J., Sandberg, D., & Nutley, S. B. (2024). Longitudinal associations between digital media use and ADHD symptoms in children and adolescents: a systematic literature review. In *European Child and Adolescent Psychiatry* (Vol. 33, Number 8, pp. 2503–2526). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s00787-022-02130-3

Ulnicane, I., & Aden, A. (2023). Power and politics in framing bias in Artificial Intelligence policy. *Review of Policy Research*, *40*(5), 665–687. https://doi.org/10.1111/ropr.12567

Vanluydt, E., van den Eijnden, R., Vonk, L., Putrik, P., van Amelsvoort, T., Delespaul, P., Levels, M., & Huijts, T. (2026). Disconnect To Reconnect: How Variations between Types of Smartphone Bans Influence Students' Well-being and Social Connectedness in Dutch Secondary Education. *Journal of Youth and Adolescence*, *55*(3), 551–569. https://doi.org/10.1007/s10964-025-02313-6

Yousef, A. M. F., Alshamy, A., Tlili, A., & Metwally, A. H. S. (2025). Demystifying the New Dilemma of Brain Rot in the Digital Era: A Review. In *Brain Sciences* (Vol. 15, Number 3). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/brainsci15030283

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: a threat to academic integrity or reformation? Evidence from multicultural perspectives. *International Journal of Educational Technology in Higher Education*, *21*(1). https://doi.org/10.1186/s41239-024-00453-6