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How AI shapes student agency and educational stratification: a qualitative interpretive meta-synthesis

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Existing research on artificial intelligence in education has largely addressed technical applications and learning outcomes while leaving sociological dimensions of AI-mediated stratification and student agency inadequately theorised. Drawing on Bourdieu's cultural capital framework, digital divide scholarship, and Yosso's Community Cultural Wealth model, this qualitative interpretive meta-synthesis examines how AI-mediated learning environments interact with established stratification mechanisms and transform student agency. Systematic searches across Scopus, Web of Science Core Collection, and ERIC identified five qualitative and mixed-methods studies encompassing 3,849 students across the United States, Norway, Israel, and China; thematic analysis followed Braun and Clarke's framework with four-analyst triangulation. Five mechanisms emerged through which AI technologies simultaneously reproduce traditional educational inequalities while generating alternative stratification forms: cultural capital mobilization through resistant, communal, and creative capital; differential engagement patterns across four distinct agency expressions; digital divide persistence and evolution; trust calibration in human-AI interaction; and educational equity implications with career dimensions. Students from underserved communities demonstrated sophisticated algorithmic bias recognition, yet gender-differentiated engagement patterns and socioeconomic disparities indicate emergent stratification with professional consequences. Lower AI trust paradoxically correlated with stronger educational outcomes, tentatively suggesting that healthy skepticism promotes more agentic learning relationships. These findings indicate that AI-mediated stratification operates through qualitative differences in how students position themselves relative to algorithmic systems and mobilize cultural resources, rather than through differential access alone, with implications for how educational institutions conceptualise equity-oriented AI integration.

KEYWORDS
artificial intelligence, cultural capital, digital divide, educational stratification, qualitative meta-synthesis, student agency

1 Introduction

1.1 Rationale

Educational technologies have historically reproduced rather than disrupted social inequalities (Reich, 2020). AI-mediated learning environments may present stratification mechanisms that differ from previous technologies. Unlike static digital tools, conversational AI systems engage students through adaptive interactions that shape not merely access to information but aspects of educational agency. Despite growing research on AI's technical capabilities and learning outcomes (Chen et al., 2020; Zawacki-Richter et al., 2019), sociological investigation of how these technologies transform student agency within existing stratification processes remains fragmented across disciplines (Williamson and Eynon, 2020). This synthesis attempts to address that gap.

Existing frameworks provide incomplete foundations for understanding AI-mediated educational stratification. Bourdieu's cultural capital theory demonstrates how educational systems convert social advantages into academic success through seemingly meritocratic processes (Bourdieu and Passeron, 1977). Digital divide research reveals that technological access fails to address educational inequality when usage patterns reflect underlying social capital disparities (Robinson et al., 2015; van Dijk, 2020). Yet these frameworks presuppose technologies as instruments deployed by human actors. AI systems with conversational capabilities challenge this instrumentalist assumption. When algorithms engage students in extended dialogues and adapt to individual patterns, the boundary between tool and educational actor becomes less clear (Knox, 2019; Williamson, 2017). Training data and algorithmic processes embed cultural codes that may align differentially with the capital students bring from diverse backgrounds (Benjamin, 2019; Noble, 2018). Decolonial scholarship extends this concern, arguing that AI systems require examination not only for algorithmic bias but for the deeper power structures and epistemological assumptions they encode, which may systematically disadvantage students from non-dominant cultural contexts (Langeveldt and Pietersen, 2024).

Three interconnected gaps emerge from this literature. First, insufficient attention to AI as participant rather than tool limits understanding of how algorithmic systems shape educational relationships. Second, limited understanding of how algorithmic interaction shapes student agency over time obscures developmental processes through which students position themselves relative to AI systems. Third, fragmented knowledge about AI-specific forms of cultural capital prevents synthesis of how differential engagement patterns relate to broader educational inequalities.

Research addressing these gaps remains scattered across disciplines with varying theoretical orientations, limiting synthesis and theory development. Studies document AI benefits and challenges (Holmes et al., 2019), identify concerns about bias and differential access (Kasneci et al., 2023), and report mixed engagement patterns (Lo et al., 2024). Recent work reveals differentiated outcomes for disadvantaged learners (Møgelvang et al., 2024), yet systematic sociological synthesis remains absent. Qualitative interpretive meta-synthesis (QIMS) addresses this fragmentation by synthesizing findings from multiple qualitative studies to develop theoretical understanding across diverse contexts (Aguirre and Bolton, 2013b).

1.2 Objectives

This synthesis examines two interconnected questions: What shapes student agency in AI-mediated environments compared to traditional educational technologies, and how do these technologies interact with existing educational stratification processes? These questions address the social, cultural, and political dimensions of technology in education, particularly regarding equity and social justice.

The analysis offers three contributions to existing scholarship. First, it explores frameworks for understanding AI as participant in stratification processes rather than neutral tool. Second, it examines mechanisms of agency transformation through algorithmic interaction, suggesting how students develop positioning strategies rather than simply acquiring technical skills. Third, it identifies forms of cultural capital that appear specific to AI engagement and operate alongside traditional educational resources.

Through systematic synthesis of five studies encompassing 3,849 students across the United States, Norway, Israel, and China, the analysis identifies five mechanisms through which AI technologies appear to simultaneously reproduce traditional inequalities and create alternative stratification forms: cultural capital mobilization, differential engagement patterns, digital divide evolution, trust calibration in human-AI interaction, and educational equity implications. These mechanisms suggest that AI-mediated education may generate stratification through qualitative differences in how students position themselves relative to algorithmic systems and mobilize cultural resources in AI interaction.

The following sections detail the methodological approach, present findings organized around five themes with empirical grounding in student experiences, discuss theoretical implications for understanding educational technology as embedded in stratification processes, and identify directions for further research.

2 Method

This synthesis employs qualitative interpretive meta-synthesis (QIMS) to develop theoretical understanding of student agency transformation and educational stratification in AI-mediated learning environments. QIMS synthesizes findings from multiple qualitative studies to generate conceptual frameworks transcending individual contexts (Aguirre and Bolton, 2013b; Noblit and Hare, 1988). This approach appears appropriate for examining emergent phenomena where research remains fragmented across disciplines.

2.1 Systematic search and selection

Search strategy development was guided by the Population, Concept, and Context (PCC) framework, commonly used in qualitative evidence syntheses to specify populations of interest, key concepts under investigation, and contextual parameters (Peters et al., 2020). Electronic searches were conducted in August 2025 across Scopus, Web of Science Core Collection, and ERIC databases selected for comprehensive coverage of educational technology research.

The search strategy employed Boolean combinations of three concept areas: AI technology terms ("artificial intelligence" OR "AI" OR "generative AI" OR "GenAI" OR "intelligent tutor*" OR "educational AI" OR "AI tutor*" OR "large language model*" OR "LLM*" OR "ChatGPT" OR "AI literacy"), educational context terms ("education*" OR "student*" OR "classroom" OR "academic" OR "school*" OR "university" OR "college"), and stratification or agency concepts ("student agency" OR "educational stratification" OR "cultural capital" OR "educational inequality" OR "educational equity" OR "digital divide" OR "habitus" OR "social class" OR "social reproduction" OR "technological capital").

The search string development followed iterative refinement to balance comprehensiveness with precision. Combining all three concept areas proved necessary to avoid retrieving either purely technical AI studies lacking educational focus or general education studies without AI specificity. The stratification and agency terms derive from established sociological frameworks to identify studies engaging with social dimensions rather than purely pedagogical concerns. The temporal scope (2018–2025) captures research following recent large language model advances. Searches limited to English-language articles, conference papers, and reviews yielded 750 records. After removing 228 duplicates, 522 records remained for screening.

Four researchers independently screened 54 randomly selected records against inclusion criteria, achieving Fleiss's kappa of 0.913. Subsequent screening resulted in 488 exclusions, leaving 34 studies for full-text evaluation. Inclusion criteria required studies examining AI technologies in K-12 or higher education with qualitative or mixed-methods approaches addressing student agency, educational stratification, or cultural capital formation across social groups. Full-text evaluation resulted in five studies meeting requirements (Table 1). The primary exclusion reason was lack of explicit attention to social stratification dimensions or differential patterns across student groups.

The five included studies encompass 3,849 students across the United States (Cao et al., 2025; Zhang et al., 2024), Norway (Møgelvang et al., 2024), Israel (Hadar Shoval, 2025), and China (Yang et al., 2024). Studies examined different AI technologies (DALL-E, ChatGPT, GreatGPT, conversational AI) across educational levels (grades 3–11, undergraduate, postgraduate) and institutional settings. For mixed-methods studies, quantitative components provided context while qualitative components constituted primary data for thematic synthesis.

2.2 Analytical approach

Four triangulation approaches were implemented (Patton, 2002). Method triangulation incorporated interviews, surveys, observations, chat logs, and reflective journals. Methodological triangulation incorporated critical pedagogy (Cao et al., 2025), case study approaches (Hadar Shoval, 2025), mixed-methods designs (Møgelvang et al., 2024; Zhang et al., 2024), and student agency frameworks (Yang et al., 2024). Source triangulation included varied educational contexts, geographic locations, and student populations. Analyst triangulation was implemented with four researchers independently conducting thematic analysis before collaborative sessions. The synthesis authors had not conducted any included studies.

Thematic analysis used a distributed approach. FM analyzed Cao et al. (2025) and Hadar Shoval (2025); GM analyzed Møgelvang et al. (2024); AN analyzed Yang et al. (2024); GB analyzed Zhang et al. (2024). Each researcher conducted independent inductive thematic analysis following Braun and Clarke's (2006) framework. Theme extraction involved line-by-line coding using each study's language and conceptual frameworks to preserve original interpretations.

Cross-study synthesis occurred through collaborative sessions comparing individual interpretations and translating them into overarching themes through constant comparative analysis

TABLE 1 Studies included in the sample.

Study	Tradition/Data Collection Method	N	Age, Years	Race/Ethnicity Gender	Volunteer Setting
Cao et al., 2025	Critical pedagogy/Interviews and observations	26	Grades 3–11 (≈8–17 years)	11 female, 15 male; Majority people of color; All from underserved communities	Public libraries and Boys & Girls Club
Hadar Shoval, 2025	Case study/Mixed-methods (surveys, interviews, reflective journal)	110 (surveys), 20 (interviews)	First-year undergraduates (≈18–22 years)	90% female, 10% male; 67.3% Jewish, 32.7% minorities; 30% first-generation	Peripheral college in northern Israel
Møgelvang et al., 2024	Mixed-methods concurrent/Surveys and open-ended questions	2,692 (total), 2,380 (gender analysis)	17.8% ≤ 20, 44.5% 21–24, 37.8% ≥ 25 years	55.2% women, 44.8% men; Norwegian students	Norwegian university college (four faculties)
Yang et al., 2024	Mixed-methods/Interviews, chat logs, reflective journals	74	Postgraduate students (≈22–28 years)	66% female, 34% male; Chinese students; 53% had research experience	Three Chinese universities (Ethnography course)
Zhang et al., 2024	Quantitative survey/Structural equation modeling	947	18–35 years (M = 27.1, SD = 5.3)	36.7% male, 61.2% female; 53.5% White, 20.8% Black, 12.1% Hispanic, 8.6% Asian; 50.2% first-generation	U.S. college students (national sample)

(Noblit and Hare, 1988). Analysis showed patterns suggesting both reinforcement of traditional inequalities and emergence of alternative stratification forms. Synthesis continued through iterative cycles until no new theoretical insights emerged. Disagreements were resolved through return to original data and discussion until consensus was achieved.

Limitations include the small number of studies ($n = 5$) reflecting emerging research on AI-mediated education from sociological perspectives. Geographic concentration in Western contexts (United States, Norway, Israel) with one East Asian study (China) limits generalizability. English-language restriction may have omitted relevant research. Methodological heterogeneity, while enabling triangulation, required interpretive translation involving analytical judgment. These limitations are offset by systematic sampling, multiple triangulation layers, and explicit documentation of analytical processes. The small sample size is consistent with established QIMS practice: Aguirre and Bolton's (2013 a) worked example of the method synthesized precisely five qualitative studies, demonstrating that theoretically grounded conclusions can emerge from comparably constrained corpora when analytical procedures are rigorously applied. The inclusion of mixed-methods studies follows the same precedent, in which qualitative findings constitute the primary synthetic material while quantitative components serve a contextualizing rather than aggregative function (Aguirre and Bolton, 2013b). The small corpus and associated limitations are addressed in Section 4.5.

Although this study employs structured database searches and systematic screening procedures, it constitutes a qualitative interpretive meta-synthesis rather than a systematic review in the methodological sense associated with that term. Reporting standards developed specifically for systematic reviews, including PRISMA guidelines, Cochrane Handbook protocols, and Campbell Collaboration standards, are therefore not applicable here. QIMS operates under distinct epistemological assumptions, prioritizing interpretive depth, theoretical translation across studies, and the generation of new conceptual understanding over exhaustive literature coverage or quantitative outcome aggregation (Aguirre and Bolton, 2013b; Noblit and Hare, 1988).

3 Findings

The synthesis reveals five interrelated mechanisms through which AI technologies interact with educational stratification while transforming student agency. These mechanisms emerged through cross-study analysis. Table 2 demonstrates how themes from individual studies contributed to developing these synthetic mechanisms.

Figure 1 presents a conceptual overview of these five mechanisms and the four engagement patterns identified within Mechanism 2, illustrating their proposed interrelationships within AI-mediated educational stratification processes.

3.1 Cultural capital mobilization in AI learning

Students from diverse backgrounds activated distinct forms of cultural capital when engaging with AI technologies: resistant, communal, and creative capital. These forms operated differently from traditional cultural capital configurations, indicating that AI integration creates alternative valuation systems for cultural resources.

Resistant capital appeared in students' capacity to identify and analyze algorithmic bias. Female students demonstrated sophisticated awareness of gender bias in AI-generated content. Chloe observed after using DALL-E 2 that gender-based image generation produced systematically distorted representations, while Addison traced this bias to training data reflecting historical power structures in which "*most people, at least in American history, who are famous were white men*" (Cao et al., 2025, p. 6). Students of color similarly recognized racial bias limitations. African American student Ava reflected on challenges generating self-portraits: "*it was hard to make it look like me*" (Cao et al., 2025, p. 8). This resistant capital enabled critical engagement with algorithmic bias rather than passive acceptance of AI outputs.

The theoretical significance extends beyond bias recognition. Students from marginalized backgrounds leveraged experiences with discrimination as analytical resources for evaluating AI systems, challenging deficit-oriented perspectives on digital divides. However, this advantage operates within constrained parameters. While resistant capital enables critique, it does not necessarily translate into power to reshape AI systems.

Communal capital manifested in consistent orientation toward collective benefit rather than individual advancement. Students from underserved communities envisioned AI applications serving broader communities. Ava, a refugee, designed an AI system for her future social work role to "*help her perform various tasks and to remember the names of the shelter residents*" (Cao et al., 2025, p. 8). William conceptualized AI for community empowerment, envisioning tools to "*help them practice writing essays or to see what a job interview would be like*" (Cao et al., 2025, p. 8). This communal orientation contrasted with individualistic approaches documented in other contexts.

Creative capital emerged through innovative reinterpretation of AI tools beyond intended purposes. Students generated new activities and pedagogical approaches through playful experimentation. Participants "*discovered that placing water bottles alongside their noses caused the AI classifier to identify them as dogs*" (Cao et al., 2025, p. 9), leading to deeper understanding of AI mechanisms subsequently incorporated into official curriculum. This creative appropriation demonstrates agency through transformation rather than mere consumption of AI capabilities.

Cultural capital mobilization varied across contexts. Hadar Shoval (2025) found that "*cultural capital influences students' starting point when they begin their higher education, including understanding the academic "rules of the game"*" (p. 2). Students with higher traditional cultural capital demonstrated greater facility in leveraging AI tools strategically, while those with less capital required scaffolded support to activate existing assets effectively. This suggests that AI integration may simultaneously create opportunities for alternative capital mobilization while reinforcing advantages associated with traditional cultural capital.

TABLE 2 Translation of themes.

New, overarching theme	Extracted, original themes with authors and publication year
Cultural capital mobilization in AI learning	Communal capital for community well-being (Cao et al., 2025)
	Creative capital in AI learning activities (Cao et al., 2025)
	Cultural and technological capital disparities (Hadar Shoval, 2025)
	Cultural capital mobilization in AI literacy (Cao et al., 2025)
	Resistant capital and AI bias recognition (Cao et al., 2025)
Differential AI engagement patterns	Academic support vs. displacement activities (Zhang et al., 2024)
	AI engagement patterns (Hadar Shoval, 2025)
	AI-enhanced cognitive flexibility (Hadar Shoval, 2025)
	Gender differences in AI chatbot usage (Møgelvang et al., 2024)
	Receptive learning approach with GenAI (Yang et al., 2024)
	Reflective learning and critical engagement (Yang et al., 2024)
	Resistive learning approach and skepticism (Yang et al., 2024)
	Resourceful learning and strategic usage (Yang et al., 2024)
Digital divide persistence and evolution	AI literacy divide emergence (Hadar Shoval, 2025)
	Digital divide persistence in AI era (Zhang et al., 2024)
	SES influences on AI literacy and usage (Zhang et al., 2024)
	Social reproduction through technology (Møgelvang et al., 2024)
Trust and agency in human-AI interaction	Academic support and trust development (Hadar Shoval, 2025)
	Collaborative researcher-student relationships (Cao et al., 2025)
	Student agency in AI-mediated learning (Yang et al., 2024)
	Trust and independent thinking concerns (Møgelvang et al., 2024)
	Trust moderation of AI relationships (Zhang et al., 2024)
Educational equity and career implications	Career relevance perceptions (Møgelvang et al., 2024)
	Communal capital for community well-being (Cao et al., 2025)
	Diversity competence and critical perspectives (Møgelvang et al., 2024)
	Educational equity implications (Hadar Shoval, 2025)
	Educational outcome disparities (Zhang et al., 2024)
	Resourceful and reflective learning advantages (Yang et al., 2024)

3.2 Differential AI engagement patterns

Students demonstrated four distinct engagement patterns representing qualitatively different expressions of agency: receptive, resistive, resourceful, and reflective approaches. These patterns appeared across studies in varied contexts, suggesting systematic rather than idiosyncratic variations in how students position themselves relative to AI systems.

Receptive engagement emphasized efficiency over critical interaction. Student Qin described initial AI encounters: "*I think it significantly promotes human learning. It would provide answers within seconds, which greatly shortened our time and reduced our efforts*" (Yang et al., 2024, p. 825). This approach positioned AI as authoritative knowledge source requiring minimal interrogation. While receptive engagement enabled rapid task completion, it constrained opportunities for developing critical evaluation capabilities or metacognitive awareness.

Resistive engagement actively questioned AI capabilities and limitations. Student Sun described testing AI reliability and finding systematic failures: "*Later, I consulted GreatGPT some statistics questions and it provided wrong answers to me. The wrong answers it provided make me doubt about its trustworthiness*" (Yang et al., 2024, p. 824). This skepticism led some students to abandon AI tools entirely. Resistive engagement preserved critical autonomy but potentially foreclosed access to legitimate AI capabilities that might support learning.

Resourceful engagement strategically leveraged AI while maintaining control over learning processes. Student Cao exemplified this approach: "*With more practice, I found that the instruction is the key to obtain the desired results and answers*" (Yang et al., 2024, p. 825). These students learned to optimize AI interactions through iterative refinement. Resourceful engagement demonstrated sophisticated positioning strategies that balanced AI utilization with human agency preservation.

Reflective engagement positioned AI as thinking partner rather than answer source. Student Hao described this relationship: "*I think GreatGPT could be first positioned as a "listener" in my study. By receiving my ideas and framework, it*

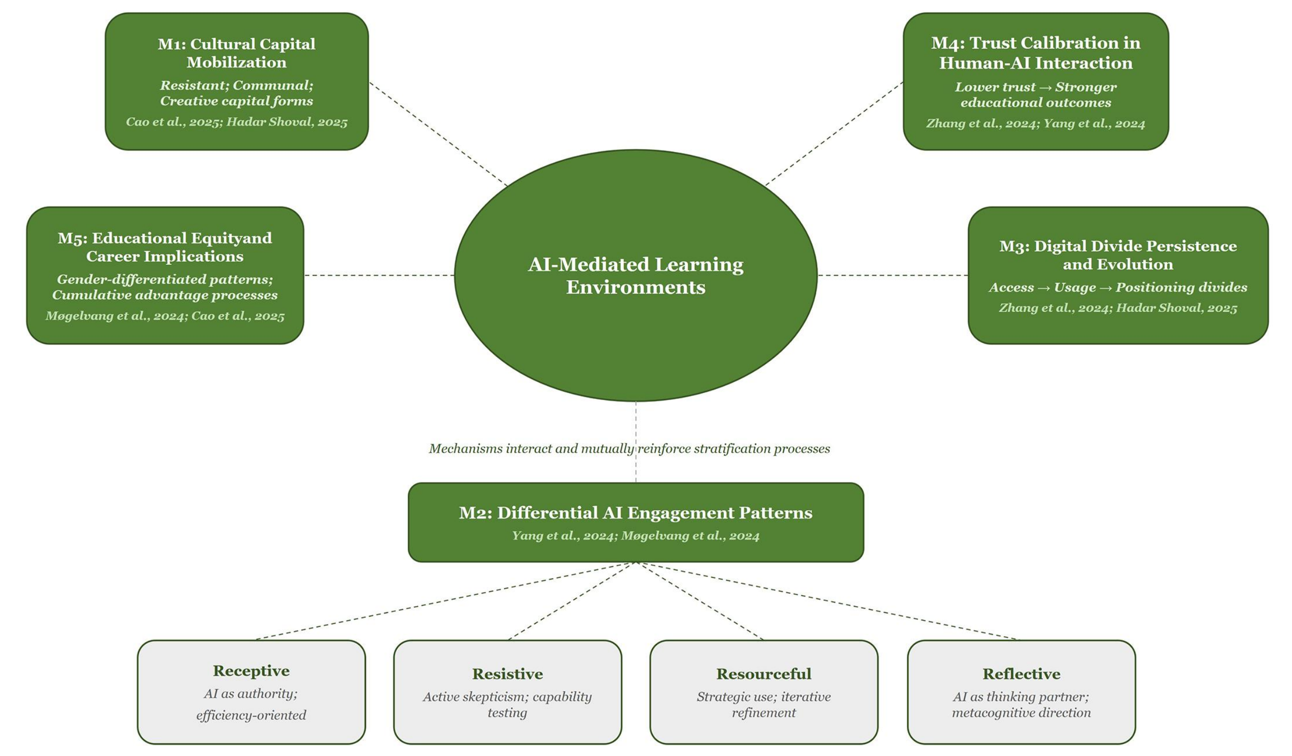

FIGURE 1
Conceptual framework. Five mechanisms of AI-mediated educational stratification and four differential engagement patterns.

sorts out my thoughts. Then it could be regarded as a "knowledge extender"" (Yang et al., 2024, p. 826). This approach integrated AI into metacognitive processes while maintaining human direction of learning trajectories.

These engagement patterns appeared influenced by but not determined by demographic characteristics. Gender differences emerged prominently. Møgelvang et al. (2024) found that "*men use genAI chatbots more frequently and point to more areas of use*" (p. 12). Male students expressed broader instrumental applications while female students demonstrated more focused but critically aware usage: "*AI offers an opportunity to gain inspiration and ideas, guidelines and advice, but it's also not something to be blindly trusted*" (Møgelvang et al., 2024, p. 11). This gendered pattern suggests emerging career preparation disparities.

Zhang et al. (2024) identified two activity dimensions: academic support and academic displacement. Support activities correlated with increased academic self-efficacy and creativity, while displacement activities showed negative associations with learning outcomes. This distinction suggests that engagement pattern quality matters more than engagement quantity for educational outcomes.

AI-enhanced cognitive flexibility emerged as differentiator across engagement patterns. Hadar Shoval (2025) documented varying capacities for "*the ability to engage with AI interfaces and manipulate ideas through them*" (p. 18). Students with higher cultural and technological capital demonstrated systematic exploration patterns, while those with less capital showed reactive patterns limited to immediate task completion. These differential patterns created compounding effects, as students developing both cognitive flexibility and strategic engagement were better positioned for advancement in AI-enhanced environments.

3.3 Digital divide persistence and evolution

Traditional digital inequalities persisted while evolving into AI-specific forms of stratification. An "*AI literacy divide*" (Hadar Shoval, 2025, p. 3) extended beyond access issues to encompass "*differential access not only to the tools themselves but also, crucially, to the skills, knowledge, and confidence required to effectively engage with AI for learning and apply AI capabilities beyond the specific course context*" (p. 17). Large effect sizes (Cohen's $d = 2.63$) for application of AI knowledge to other studies between majority and minority groups suggested fundamental differences in how students from different backgrounds conceptualize AI learning experiences.

Socioeconomic stratification manifested in AI usage patterns. Zhang et al. (2024) found that "*family SES was positively related to use for academic support ($\beta = .21$, $p < .001$), with student SES negatively associated ($\beta = -.24$, $p < .001$)*" (p. 13). Students from higher SES families demonstrated greater engagement with AI for constructive academic purposes, while those facing individual financial pressures showed patterns suggesting compensatory rather than enhancement-oriented usage. This pattern indicates that family resources continue influencing access to advanced AI-related skills even as individual financial pressure during college may drive certain forms of AI adoption.

The persistence of digital divides alongside AI-specific inequalities suggests layered rather than replaced stratification mechanisms. Zhang et al. (2024) found that student SES showed negative associations with digital literacy while family SES showed positive associations with AI literacy. This divergence indicates that students facing financial pressures may develop digital competencies through different pathways than more financially secure peers, while family resources continue shaping access to emerging AI capabilities.

Gender-based patterns suggested future workplace implications. Møgelvang et al. (2024) documented that "*if workplaces in the future favor male to female employees due to their more extensive experience with genAI chatbots and their focus on employability, it may lead to severe consequences for society*" (p. 14). Female students expressed greater concerns about AI dependency: "*I think it makes it too easy to find answers. It leads to a loss of the ability to think for oneself and critically*" (Møgelvang et al., 2024, p. 11). While this critical stance may protect intellectual autonomy, differential engagement breadth could affect professional opportunities.

Social reproduction operated through differential AI engagement. Students with higher digital proficiency demonstrated more cautious AI usage, suggesting that "*higher digital literacy may entail mastery of a greater range of digital technologies, so individuals might have used other tools serving the same purposes rather than ChatGPT*" (Zhang et al., 2024, p. 17). Existing digital advantages may initially limit AI adoption but potentially lead to more strategic long-term engagement as students evaluate AI capabilities against broader technological repertoires.

The evolution of digital divides manifested in emergent forms of cultural capital. Students who successfully navigated AI tools developed understanding not merely of how to use AI but when, why, and in what contexts it provides educational value. This AI cultural capital appeared unevenly distributed across traditional demographic lines while creating new categories of advantage and disadvantage that intersect with but do not perfectly reproduce existing inequalities.

3.4 Trust and agency in human-AI interaction

Trust emerged as fundamental mediator shaping AI educational relationships and agency expression. Zhang et al. (2024) found that attitudinal trust in ChatGPT moderates relationships between student characteristics, usage patterns, and educational outcomes. Paradoxically, students with lower trust experienced stronger educational benefits from appropriate AI usage. "*Academic support had stronger associations with ASE ($\beta = .60$, $p < .001$) and creativity ($\beta = .65$, $p < .001$) under low trust than it did with ASE ($\beta = .36$, $p < .001$) and creativity ($\beta = .46$, $p < .001$) under high trust*" (p. 13). Users with low trust "*perceive more autonomy and less reliance in use and thereby tend to attribute task success to themselves, therefore receiving greater psychological gains from use*" (Zhang et al., 2024, p. 18). This suggests that healthy skepticism promotes more agentic learning relationships.

The relationship between trust and agency manifested differently across cultural contexts. Norwegian students demonstrated sophisticated trust calibration. Female participants expressed particular concern about maintaining intellectual independence: "*I think it makes it too easy to find answers. It leads to a loss of the ability to think for oneself and critically*" (Møgelvang et al., 2024, p. 11). This critical stance reflected protective agency maintaining cognitive autonomy while selectively engaging AI capabilities. Chinese students showed varying trust patterns influencing learning approaches. Student Hui "*raised the concern that an over reliance on GreatGPT in the learning process might potentially hinder the development of critical thinking skills*" (Yang et al., 2024, p. 824), leading to intentional, bounded AI engagement.

Collaborative relationships between educators and students proved important for developing appropriate trust calibration. Hadar Shoval (2025) documented how instructor support helped students develop realistic AI expectations. A first-generation minority student described: "*The lecturer said we needed to register for the free version of the AI with our Google account. I couldn't remember how to do it or what my password was, so I pretended to be practicing. But the lecturer didn't give up*" (p. 11). Scaffolded introduction helped students develop confidence without overreliance.

Cultural capital mobilization through AI interactions required collaborative researcher-student relationships beyond traditional educational hierarchies. Cao et al. (2025) found that "*it was difficult to find and integrate the unique cultural capital of underserved communities despite our efforts. Unexpectedly, we were able to identify cultural capital while running the AI literacy program*" (p. 11). The collaborative relationship proved essential: "*It is not just the literacy materials developed from researchers' knowledge and perspectives that mobilize students' cultural capital, but also the reciprocal dialogue between researchers and students*" (Cao et al., 2025, p. 11). This positioned students as co-creators rather than passive recipients.

Agency expression through AI interaction varied based on trust levels and prior experiences. Students who had experienced discrimination or educational marginalization often demonstrated sophisticated agency in AI interactions, using tools to access educational opportunities while maintaining critical awareness of limitations. Development of trust appeared linked to students' sense of control. Reflective learners positioned themselves as directors of AI engagement: "*they were deeply aware that in the human-technology relationship, human's agency dominates the ways they interact and benefit from technology*" (Yang et al., 2024, p. 826).

3.5 Educational equity and career implications

AI integration presents contradictory potentials for educational equity. Zhang et al. (2024) found that "*academic support activities had strong positive associations*" (p. 13) with both academic self-efficacy and perceived creativity, suggesting appropriate AI usage could enhance educational outcomes across student populations. However, "*displacement activities may reduce students' confidence in their own abilities to achieve academic goals or generate innovative solutions, potentially impairing their learning motivation if they perceive AI as more competent than humans*" (p. 16).

Career preparation disparities emerged through gender-differentiated engagement. Møgelvang et al. (2024) documented that "*men perceive genAI technology as more relevant to their future employment*" (p. 8). Male students expressed instrumental career perspectives: "*Chatbots are becoming increasingly integrated into our daily lives, and I believe it is essential to incorporate them into education so that students are prepared for a future where chatbots are common tools*" (Møgelvang et al., 2024, p. 11). This career-oriented framing potentially advantages male students in developing professionally relevant AI competencies.

Female students demonstrated cautious but critically sophisticated approaches: "*In general, I think that's just the way the future is, and after its release, it will be impossible to ban because there will always be ways to use it without getting caught. It is here to stay, so guidance on how to use it properly is appropriate*" (Møgelvang et al., 2024, p. 11). This perspective emphasized adaptation and ethical usage rather than enthusiastic adoption. While critical sophistication offers certain advantages, differential usage breadth could affect career opportunities.

Educational equity implications appeared particularly pronounced for underserved communities. Møgelvang et al. (2024) revealed that "*women primarily utilize genAI chatbots in text-related tasks and express greater concerns regarding critical and independent thinking*" (p. 1). These differential patterns could potentially limit access to broader AI applications providing educational and career advantages.

Long-term stratification risks emerged through cumulative advantage processes. Students developing sophisticated AI competencies early demonstrated accelerating benefits. Yang et al. (2024) observed students in resourceful and reflective categories "*showcased their resourcefulness by guiding GreatGPT to refine its output further, and strategically leveraged it to tackle more complex learning requirements*" (p. 825). Compound learning advantages could potentially widen educational gaps over time.

The synthesis also identified potential equity-enhancing mechanisms. Students from underserved communities demonstrated strengths in collaborative and community-oriented AI applications. Their communal capital orientation led to innovative applications addressing collective challenges rather than individual advancement. As documented by Cao et al. (2025), "*students often prioritized the well-being of their communities*" (p. 9) rather than personal gain.

Institutional support emerged as important for realizing AI's equity potential. Hadar Shoval (2025) suggested that "*targeted strategies to support diverse student populations in engaging with AI tools*" (p. 20) could mitigate disparities. However, Møgelvang et al. (2024) revealed that "*only 6.3% of the participants had experienced genAI chatbot training*" and "*8.6% integration of genAI chatbots in their courses*" (p. 5), indicating insufficient institutional preparation.

Career outcome implications varied based on how students positioned themselves relative to AI technologies. Students developing agentic relationships with AI tools appeared better positioned for future success. Those who either rejected AI entirely or adopted dependent relationships showed greater vulnerability to emerging educational stratification. AI's impact on educational equity appears to depend on implementation approaches, institutional support structures, and students' development of appropriate agency relationships with these technologies.

4 Discussion

The findings reveal how AI technologies transform student agency while interacting with educational stratification through mechanisms that both reproduce traditional inequalities and generate alternative forms of advantage. This section examines these findings in relation to the research questions and theoretical frameworks, identifying contributions to knowledge, theory, and methodology.

4.1 Examination of research questions

The first research question asked what shapes student agency in AI-mediated environments compared to traditional educational technologies. The synthesis suggests three mechanisms. First, conversational and adaptive capabilities enable students to develop positioning strategies rather than simply operating tools. The four engagement patterns (receptive, resistive, resourceful, reflective) represent agency expressions that develop through interaction rather than existing as fixed characteristics. Students moved between patterns based on task context, trust levels, and accumulated experience, suggesting agency operates as dynamic positioning rather than stable attribute.

Second, trust calibration emerged as central to agency development in ways not documented with traditional technologies. The paradoxical finding that lower trust correlated with stronger educational benefits challenges assumptions that technology adoption requires confidence. Instead, healthy skepticism appeared to promote agentic relationships by maintaining students' sense of control. This differs from traditional technologies where trust typically correlates positively with effective usage. Technology acceptance frameworks have long conceptualized trust as a prerequisite for effective use (Davis, 1989), which makes this reversal particularly significant for how institutions approach AI integration pedagogically. AI's conversational capabilities create perceived partnership dynamics that may undermine agency when trust becomes excessive, positioning AI as authoritative rather than instrumental.

Third, cultural capital mobilization patterns suggest AI engagement privileges certain forms of knowledge in ways differing from traditional technologies. Resistant capital, derived from experiences with marginalization, enabled sophisticated algorithmic bias critique. This challenges instrumentalist assumptions by revealing that AI systems embed cultural codes students must navigate rather than simply deploy. As Benjamin (2019) and Noble (2018) argue, algorithmic systems encode social arrangements rather than neutrally mediating knowledge, meaning that students' capacity to recognize and critique these arrangements may itself constitute a form of critical capital. The patterns observed in this synthesis tentatively suggest that marginalization may, under certain conditions, function as an analytical resource, though this possibility operates within constrained parameters and requires further empirical grounding.

The second research question asked how AI technologies interact with existing educational stratification processes. Three patterns emerged. First, traditional stratification mechanisms persist through AI-mediated education. Socioeconomic status continued shaping access to AI literacy development, with family resources predicting academic support usage while individual financial pressure predicted compensatory engagement. Gender patterns suggest emerging career preparation disparities, with male students demonstrating broader instrumental engagement while female students showed more focused but critically cautious usage. These patterns indicate AI integration reproduces existing inequalities through differential engagement quality rather than access alone.

Second, AI technologies create alternative stratification mechanisms that intersect with but do not perfectly reproduce traditional demographic patterns. The emergence of AI cultural capital as distinct from general digital literacy suggests new forms of advantage combining technical facility with critical evaluation capabilities. Large effect sizes for minority-majority differences in applying AI knowledge beyond specific contexts indicate fundamental disparities in how students from different backgrounds conceptualize AI learning experiences. This suggests AI integration generates stratification through differential capacity to transfer and generalize engagement rather than merely through usage patterns.

Third, cumulative advantage processes operate through AI engagement in ways that may accelerate inequality over time. Students developing sophisticated positioning strategies early demonstrated compound benefits through enhanced cognitive flexibility and strategic engagement. The combination of resourceful and reflective approaches appeared to create self-reinforcing cycles where successful engagement enabled more complex applications, potentially widening gaps between students who develop agentic relationships and those who adopt dependent or resistant stances.

4.2 Theoretical contextualization and conceptual contributions

The findings extend cultural capital theory by identifying AI-specific forms of capital operating alongside traditional educational resources. Bourdieu's framework illuminates how educational systems convert social advantages into success through meritocratic processes (Bourdieu and Passeron, 1977), but presupposes technologies as instruments. The identification of resistant, communal, and creative capital forms suggests AI-mediated education requires extension of cultural capital theory to account for how algorithmic systems embed assumptions about knowledge that align differentially with diverse cultural resources.

The patterns observed raise the possibility that, under certain conditions, marginalization may function as an analytical resource, with critical evaluation of algorithmic bias representing a potential form of educational advantage for students from non-dominant backgrounds. This extends Yosso's (2005) Community Cultural Wealth framework into digital environments. However, the finding also reveals constraints. While resistant capital enables critique, it does not necessarily translate into power to reshape AI systems. This suggests AI integration may create what might be termed "constrained capital mobility", where certain forms gain recognition without fundamentally disrupting existing hierarchies.

The identification of communal capital orientation among students from underserved communities challenges individualistic assumptions embedded in educational technology research. Students consistently envisioning AI applications for collective benefit rather than individual advancement suggests cultural assets from non-dominant communities may align differently with AI usage than dominant cultural capital. This has implications for how institutions approach AI literacy development. Curricula emphasizing individual skill acquisition may fail to recognize and leverage communal orientation as valuable approach.

The findings also extend digital divide research by revealing second-level divides in AI-mediated contexts. Robinson et al. (2015) demonstrated that differential usage patterns reflect cultural and social capital differences even when access exists. The synthesis suggests AI technologies create third-level divides through differential capacity for transfer and generalization. The distinction between students who develop cognitive flexibility enabling application across contexts vs. those whose engagement remains reactive indicates qualitative differences transcending both access and usage patterns. These patterns may point toward a progression from access divides (first-level) through usage divides (second-level) to what could tentatively be characterized as positioning divides (third-level), in which students appear to develop qualitatively different relationships with algorithmic systems, though this conceptualization remains provisional and requires further empirical examination.

The four engagement patterns contribute a framework moving beyond binary distinctions between users and non-users. This builds on Robinson et al. (2015) work on digital engagement quality while revealing AI-specific manifestations of educational agency. The progression from receptive to reflective engagement suggests developmental trajectory, though findings indicate some students remain in receptive or resistive patterns. This raises questions about whether engagement patterns reflect inherent preferences, resource constraints, or educational scaffolding opportunities.

The paradoxical relationship between trust and educational outcomes challenges assumptions about technology adoption and effective usage. The finding that lower trust correlated with stronger educational benefits suggests different dynamics in AI-mediated contexts. This may reflect what Knox (2019) terms the "postdigital" condition where boundaries between human and technological agency become ambiguous. When AI systems possess conversational capabilities creating partnership illusions, excessive trust may undermine human agency by shifting attribution for learning accomplishments from student to system. This suggests effective AI integration requires pedagogical approaches supporting skepticism rather than promoting uncritical adoption.

The synthesis also reveals how AI technologies participate in educational processes rather than serving as neutral instruments. Williamson (2017) argues that algorithmic systems shape educational relationships through embedded assumptions about learning and knowledge. The finding that training data and algorithmic processes embed cultural codes aligning differentially with diverse student backgrounds supports this perspective while providing empirical grounding. The identification of specific mechanisms (resistant capital recognition of bias, differential engagement patterns, trust calibration) through which this participation operates contributes to understanding how algorithmic agency intersects with student agency in educational contexts.

4.3 Research gaps addressed and knowledge contributions

This study addresses three gaps identified in the literature. First, insufficient theoretical attention to AI as participant rather than tool limited understanding of how algorithmic systems actively shape educational relationships. The synthesis provides frameworks for understanding AI participation through identification of specific mechanisms: cultural capital mobilization, differential engagement patterns, and trust mediation. These mechanisms suggest AI systems transform educational processes by introducing algorithmic agency students must navigate.

Second, limited understanding of how algorithmic interaction shapes student agency over time obscured developmental processes. The identification of four engagement patterns that students move between reveals agency development as dynamic positioning rather than static skill acquisition. This contributes understanding of how sustained AI interaction shapes student dispositions and practices, particularly regarding trust calibration and positioning strategies.

Third, fragmented knowledge about AI-specific forms of cultural capital prevented synthesis of how differential engagement relates to broader inequalities. The identification of resistant, communal, and creative capital forms contributes understanding of how diverse cultural resources translate into AI-mediated educational advantages and disadvantages. The finding that marginalization can become analytical resource while simultaneously operating within constrained parameters reveals complexity in how AI integration affects educational equity.

The synthesis also contributes methodological insights about QIMS application to emerging technology fields. The fragmentation of research across disciplines limited previous synthesis attempts. The approach of maintaining conceptual integrity of individual studies while translating across frameworks enabled identification of convergent patterns transcending particular theoretical orientations.

4.4 Implications for theory, methodology, and application

The findings suggest several theoretical implications. Cultural capital theory requires extension to account for algorithmic participation in educational processes. The identification of AI-specific capital forms suggests Bourdieu's framework needs supplementation to address how algorithmic systems embed assumptions requiring navigation with diverse cultural resources. This extension might involve conceptualizing what could be termed "algorithmic capital" encompassing capacity to position oneself strategically relative to AI systems while maintaining critical awareness of limitations.

Digital divide theory requires attention to third-level divides involving positioning and transfer capabilities rather than access or usage alone. Large effect sizes for minority-majority differences in applying AI knowledge across contexts suggest fundamental disparities in how students conceptualize AI learning experiences. This points toward need for frameworks addressing differential capacity for abstraction and generalization.

Agency theory in educational contexts requires frameworks accounting for dynamic positioning in relation to algorithmic systems with conversational capabilities. Existing frameworks emphasize autonomous action and strategic decision-making (Biesta and Tedder, 2007; Emirbayer and Mische, 1998) but do not address agency development through sustained interaction with systems possessing embedded assumptions. The four engagement patterns contribute preliminary framework for understanding agency as positioning strategy developed through interaction rather than inherent attribute.

Methodological implications include recognition that QIMS enables synthesis of fragmented research fields through translation across theoretical frameworks. The approach of preserving individual study integrity while identifying convergent patterns may prove valuable for other emerging technology areas where disciplinary fragmentation limits theory development.

Practical implications center on recognition that AI integration initiatives must address both traditional digital divides and AI-specific stratification mechanisms. The findings suggest effective AI integration requires several approaches. First, pedagogical support for developing appropriate trust calibration rather than promoting uncritical adoption. The paradoxical finding that lower trust correlates with stronger educational benefits indicates skepticism should be cultivated. Second, recognition and leveraging of diverse forms of cultural capital rather than deficit-oriented approaches. The identification of resistant, communal, and creative capital suggests students from underserved communities possess analytical capabilities that can become educational advantages when recognized and supported. Third, attention to engagement pattern development rather than technical skill acquisition alone. The progression from receptive to reflective engagement suggests supporting students' development of positioning strategies may prove more important than teaching AI operation.

The finding that institutional support remains insufficient (6.3% training, 8.6% course integration) suggests need for systematic AI integration planning. However, this integration must avoid technological solutionism assuming AI inherently benefits all students equally. The identification of mechanisms through which AI reproduces inequalities while creating alternative stratification forms indicates implementation approaches significantly affect equity outcomes.

4.5 Limitations and directions for further research

Several limitations affect these findings. The small number of included studies reflects emerging nature of sociological research on AI-mediated education. While 3,849 participants across four countries provide empirical grounding, geographic concentration in Western contexts limits generalizability. The exclusion of non-English studies may have omitted relevant research. Methodological heterogeneity, while enabling triangulation, required interpretive translation involving analytical judgment.

These findings suggest several research directions. First, longitudinal investigation of how engagement patterns develop over time and whether students progress from receptive toward reflective approaches or remain in particular patterns. Second, examination of institutional and pedagogical factors supporting or constraining this progression. Third, investigation of how resistant, communal, and creative capital forms operate across different AI technologies and educational contexts. Fourth, exploration of how trust calibration develops and whether pedagogical interventions can support appropriate skepticism while avoiding technological rejection. Fifth, examination of how AI-specific cultural capital intersects with traditional forms across diverse cultural contexts.

The findings also raise questions about optimal trust levels for different educational contexts and student populations. The paradoxical relationship between trust and outcomes suggests complex dynamics requiring further investigation. Additionally, the mechanisms through which marginalization becomes analytical resource while operating within constrained parameters require examination to understand whether and how educational institutions might leverage resistant capital without reinforcing deficit perspectives. The gender-differentiated engagement patterns suggesting career preparation disparities require longitudinal investigation of how early AI experiences shape professional trajectories.

5 Conclusions

This synthesis examined how AI technologies transform student agency while interacting with educational stratification processes. Through systematic analysis of five studies encompassing 3,849 students across four countries, the investigation identified five mechanisms through which AI-mediated education simultaneously reproduces traditional inequalities and generates alternative stratification forms. These mechanisms reveal that AI integration affects educational equity not primarily through differential access but through qualitative differences in how students position themselves relative to algorithmic systems and mobilize diverse cultural resources.

The analysis contributes to understanding educational technology as embedded in social stratification processes. Three theoretical contributions emerge. First, the identification of resistant, communal, and creative forms of cultural capital demonstrates how students from diverse backgrounds bring assets to AI-mediated learning that may be overlooked by approaches focused on technical skill development. The finding that marginalization can become analytical resource for evaluating algorithmic bias challenges deficit-oriented perspectives while revealing this advantage operates within constrained parameters. Second, the four engagement patterns (receptive, resistive, resourceful, reflective) provide a framework for understanding AI interaction as dynamic positioning. Students moved between these patterns based on context and experience, suggesting agency development involves learning to position oneself strategically. Third, the paradoxical finding that lower trust correlates with stronger educational benefits challenges assumptions about technology adoption, suggesting healthy skepticism promotes agentic learning relationships.

The synthesis reveals how AI technologies participate in educational stratification through mechanisms differing from previous technologies. The emergence of what might be termed third-level digital divides, involving differential capacity for transfer and generalization rather than access or usage alone, suggests AI integration creates new forms of advantage intersecting with but not perfectly reproducing traditional demographic patterns. Large effect sizes for minority-majority differences in applying AI knowledge across contexts indicate fundamental disparities in how students from different backgrounds conceptualize AI learning experiences. Gender-differentiated engagement patterns, with male students demonstrating broader instrumental applications while female students show more focused but critically aware usage, suggest emerging career preparation disparities.

These findings have implications for how educational institutions approach AI integration. The identification of mechanisms through which AI reproduces inequalities while creating alternative stratification indicates implementation approaches significantly affect equity outcomes. Pedagogical support for developing appropriate trust calibration rather than promoting uncritical adoption appears important, as does recognition and leveraging of diverse forms of cultural capital. The finding that only 6.3% of students in one study had received AI training while 8.6% experienced course integration suggests current institutional responses remain insufficient.

The synthesis also demonstrates methodological value of QIMS for examining emerging technology fields where research remains fragmented across disciplines. The approach of maintaining conceptual integrity of individual studies while translating across frameworks enabled identification of convergent patterns transcending particular theoretical orientations.

Several limitations affect these findings. The small number of included studies reflects emerging nature of sociological research on AI-mediated education. Geographic concentration in Western contexts limits generalizability. The exclusion of non-English language studies may have omitted relevant research. These limitations suggest need for continued investigation as research develops.

The findings point toward several directions for further research. Longitudinal investigation of how engagement patterns develop over time could illuminate whether students progress from receptive toward reflective approaches. Examination of institutional and pedagogical factors supporting or constraining this progression would inform equitable AI integration efforts. Investigation of how resistant, communal, and creative capital forms operate across different AI technologies and educational contexts could extend understanding of cultural resources in AI-mediated learning.

The analysis suggests AI integration in education requires attention to how algorithmic systems participate in rather than simply support educational processes. When AI technologies embed cultural codes aligning differentially with diverse student backgrounds, educational equity depends not merely on providing access but on supporting students' development of positioning strategies that maintain agency while engaging AI capabilities. The identification of forms of cultural capital specific to AI-mediated contexts, engagement patterns representing different agency expressions, and trust as mediator of educational relationships contributes frameworks for understanding how emerging technologies reshape educational stratification processes.

Data availability statement

Publicly available datasets were analyzed in this study. The dataset of included studies, comprising study characteristics, extracted themes, and synthesis documentation, is publicly available on Zenodo at https://doi.org/10.5281/zenodo.18893208 (Manganello et al., 2026). The five primary studies analyzed in this meta—synthesis are publicly available peer—reviewed articles accessible through their respective publishers at the following DOIs: https://doi.org/10.1145/3706598.3713173; https://doi.org/10.3390/educsci15050637; https://doi.org/10.3390/educsci14121363; https://doi.org/10.1080/03075079.2024.2327003; https://doi.org/10.1177/14614448241301741. Complete bibliographic information is provided in the References section of the manuscript.

Author contributions

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