Exploring the Potential of Artificial Intelligence in Reducing Learning Resistance in Education

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in educational environments through adaptive learning systems, intelligent tutoring, learning analytics, automated feedback, and generative AI applications. These technologies may help learners who experience difficulty, anxiety, low confidence, disengagement, or a perceived mismatch between instructional demands and their learning needs. Nevertheless, the claim that AI reduces learning resistance requires conceptual precision and critical scrutiny. Learning resistance is not treated here as a fixed learner deficit or a synonym for laziness; rather, it is conceptualised as a context-sensitive pattern of reluctance, avoidance, opposition, or reduced participation that may emerge through interactions among cognitive demands, emotional experiences, motivation, behaviour, social relations, and institutional conditions. This paper develops a structured conceptual review of literature on AI in education, learner motivation and engagement, adaptive learning, generative AI, and responsible educational technology. The review is organised thematically around five dimensions of learning resistance: cognitive, emotional, behavioural, motivational, and sociocultural. Evidence from reviews and empirical studies suggests that adaptive support, timely feedback, opportunities for low-stakes practice, and learner-responsive explanations may create conditions conducive to engagement. However, these outcomes are neither automatic nor uniform. Inaccurate outputs, opaque recommendations, excessive cognitive demands, privacy risks, algorithmic bias, compulsory use, unequal access, and reduced learner agency may intensify resistance. The paper argues that AI should be understood as a conditional pedagogical resource rather than an independent solution to disengagement. Its educational value depends on instructional design, teacher mediation, learner agency, accessibility, and institutional safeguards. The paper concludes with a conceptual synthesis framework, implications for secondary education, methodological limitations, and priorities for empirical research that directly measures learning resistance rather than inferring it from achievement or engagement alone.

Keywords: Artificial Intelligence; Learning Resistance; Learner Engagement; Adaptive Learning; Generative AI; Learner Motivation; Human-Centred Education

INTRODUCTION

Artificial intelligence has become a prominent feature of contemporary educational debate because it can support the organisation of learning resources, the interpretation of learner responses, the generation of explanations, and the provision of feedback. Educational applications range from intelligent tutoring systems and adaptive practice environments to predictive analytics and conversational generative AI. Reviews of AI in education show that the field encompasses diverse technologies, educational settings, and research purposes rather than a single uniform intervention (Wang et al., 2024; Zawacki-Richter et al., 2019). As these tools become more accessible, an important question is not only whether they improve test performance, but also whether they help learners participate in learning when they encounter difficulty, uncertainty, anxiety, or low perceived relevance.

Learning requires more than exposure to information. Students must interpret ideas, tolerate uncertainty, attempt challenging tasks, respond to feedback, and sustain effort when understanding is incomplete. Learners

may withdraw when the instructional pace is too rapid, explanations do not connect with prior knowledge, errors are experienced as humiliation, or classroom tasks appear unrelated to their goals. Such responses can be mistaken for unwillingness or indiscipline when their origins lie partly in the learning environment. A contextual perspective is therefore essential: resistance may express an attempt to protect oneself from repeated failure, social embarrassment, excessive cognitive demand, or an instructional arrangement that does not provide meaningful choice.

The possible contribution of AI lies in its capacity to offer additional explanations, vary task difficulty, provide practice opportunities, and make feedback available beyond the immediate teacher–learner interaction. Adaptive systems may respond to learner performance, while conversational tools can allow students to ask questions privately or request alternative examples. Research on AI-supported adaptive learning and ChatGPT-mediated engagement provides reasons to investigate these possibilities, but it also shows that effects depend on context, design, and the outcome being measured (Lo et al., 2024; Wang et al., 2024). Increased use of a tool cannot automatically be interpreted as reduced resistance, and improved achievement alone does not establish that cognitive, emotional, or social barriers have diminished.

A further concern is that AI can itself become a source of resistance. Students may encounter inaccurate explanations, intrusive data collection, confusing interfaces, inaccessible platforms, or pressure to use a tool they do not trust. UNESCO (2023) consequently emphasises human-centred, age-appropriate, safe, equitable, and meaningful approaches to generative AI in education. Recent research on enforced AI learning environments also draws attention to negative technological experiences and the possibility that compulsory use may intensify resistance (Mohd Daud, 2026).

Against this background, this paper examines the conditions under which AI may support a more responsive learning environment and the conditions under which it may reproduce or intensify barriers. It does not assume that AI has a direct, universal, or independently established effect on learning resistance. Instead, it develops a conceptual account of the mechanisms through which AI applications might influence resistance and identifies the evidence and methodological work needed to test those mechanisms.

Objectives

The paper is guided by the following objectives:

- To clarify the concept of learning resistance and distinguish it from related constructs such as disengagement, low motivation, technology resistance, and academic difficulty.
- To examine how AI-enabled educational practices may address cognitive, emotional, behavioural, motivational, and sociocultural barriers to learning.
- To understand a conceptual synthesis linking AI applications, possible mechanisms, learning-resistance dimensions, and implementation conditions.
- To identify implications for teachers, educational institutions, policymakers, and future empirical research.

Conceptualising Learning Resistance

Definition and boundaries of the construct

For this paper, learning resistance refers to a context-sensitive pattern of reluctance, avoidance, opposition, or reduced participation in learning activities when learners perceive demands, experiences, relationships, or outcomes as difficult, threatening, irrelevant, inaccessible, or inconsistent with their needs. This working definition is proposed for conceptual analysis; it should not be mistaken for a universally accepted diagnostic definition. Learning resistance is not necessarily deliberate defiance. It may be visible as postponing tasks, avoiding questions, declining to attempt challenging work, disengaging after repeated errors, resisting a prescribed learning technology, or participating only minimally.

The construct overlaps with, but is not interchangeable with, motivation, engagement, persistence, academic achievement, or technology acceptance. Motivation concerns the reasons and intensity of goal-directed action;

engagement commonly refers to behavioural, emotional, cognitive, and sometimes social participation; achievement concerns demonstrated learning outcomes. Resistance is the pattern of reluctance or opposition that may interfere with participation. A student may achieve well while resisting a compulsory platform, or may appear engaged while still experiencing anxiety and low confidence. Consequently, resistance should be measured directly rather than inferred from a single proxy.

The concept also requires a distinction between resistance to learning and justified resistance to a particular learning arrangement. A learner who questions an inaccurate AI explanation, declines unnecessary data collection, or objects to an inaccessible platform may be exercising sound judgement rather than displaying an educational deficit. An ethically adequate framework must therefore ask what the learner is resisting, why the resistance arises, and whether the learning environment itself requires change.

A Multidimensional Framework

This paper uses five analytical dimensions. They are intended as a useful organising framework for review and future measurement, not as a claim that all dimensions have already been validated as a single psychometric scale.

- Cognitive resistance: reluctance or withdrawal associated with perceived difficulty, excessive information, weak prior knowledge, unclear explanations, or an unmanageable pace.
- Emotional resistance: avoidance associated with anxiety, embarrassment, frustration, fear of failure, low confidence, or a sense of threat during learning.
- Behavioural resistance: observable non-participation, task avoidance, repeated postponement, refusal to attempt activities, or withdrawal from learning routines.
- Motivational resistance: diminished willingness to invest effort when tasks appear uninteresting, externally imposed, irrelevant, or unlikely to lead to competence or valued outcomes.
- Sociocultural resistance: reluctance shaped by language, cultural expectations, peer relationships, family circumstances, disability, unequal access, institutional power, or perceptions that the learning environment does not recognise the learner.

These dimensions can interact. For example, an inaccessible AI interface may produce cognitive difficulty, which triggers frustration, reduces perceived competence, and ultimately leads to avoidance. Conversely, a supportive explanation may reduce task difficulty and make it safer for a learner to ask questions, potentially improving confidence and participation. Such pathways are plausible hypotheses; their strength and direction require empirical testing.

THEORETICAL FOUNDATIONS

Self-Determination Theory

Self-determination theory provides a useful lens for understanding the motivational conditions under which learners participate willingly. Ryan and Deci (2020) describe autonomy, competence, and relatedness as central psychological needs relevant to motivation and well-being. In an AI-supported environment, autonomy may be supported when students can choose among appropriate examples, request explanations, or regulate the pace of practice. Competence may be supported through scaffolded tasks and informative feedback that helps learners understand how to improve. Relatedness, however, cannot be assumed to follow from personalisation: learners still need meaningful relationships with teachers and peers.

The theory also cautions against treating engagement as a simple consequence of technological novelty or external rewards. Gamification, automated reminders, or compulsory platform use may increase visible activity without supporting internalised motivation. If AI removes meaningful choice or makes learners feel monitored, it may undermine autonomy. Therefore, the relevant question is not whether a tool offers options, but whether those options provide genuine, age-appropriate control within a coherent learning design.

Cognitive Load and Instructional Support

Cognitive load theory highlights the limits of working memory during complex learning and the importance of instructional design that manages unnecessary demands (Sweller, 1988). AI-generated explanations, worked examples, staged hints, and appropriately sequenced practice may help learners process difficult material. Yet the same systems can generate lengthy, inconsistent, or overly complex responses that increase extraneous load. More information is not necessarily better instruction. AI support is most defensible when it is aligned with the learning objective, builds on prior knowledge, and gradually reduces assistance as learners become more capable.

Learning as an interaction between Learner and Environment

A contextual account of learning recognises that reluctance may emerge from the interaction between personal experience and educational conditions. Illeris (2018) presents learning as involving interacting cognitive, emotional, and social dimensions. From this perspective, learning resistance should not be attributed exclusively to an individual learner. Instructional pace, classroom climate, task relevance, language, assessment pressure, access to resources, and relationships with teachers can all shape whether participation feels possible or worthwhile.

This interactional position is important for AI integration. Predictive analytics may identify patterns of low participation, but a pattern does not explain its cause. A learner may be struggling with content, experiencing family difficulties, sharing a device, facing a language barrier, or reasonably distrusting a platform. Human interpretation and dialogue are necessary before the system's output is translated into an intervention.

Human-Centred and Responsible AI

A human-centred approach places educational purpose, learner agency, safety, equity, and accountability ahead of technological adoption for its own sake. UNESCO (2023) recommends attention to data privacy, age appropriateness, pedagogical validation, and the wider ethical implications of generative AI. This perspective complements the theories above: AI should support competence without creating dependence, provide options without coercion, and assist teachers without replacing the relational and contextual judgement required in education.

REVIEW METHODOLOGY

Review Design

This manuscript is framed as a structured conceptual review with thematic synthesis. It integrates conceptual literature on learning and motivation, research reviews on AI in education, selected empirical studies of adaptive learning and student engagement, and international guidance on responsible generative AI. Its purpose is to clarify concepts, compare proposed mechanisms, and identify gaps in the evidence. It is not presented as a registered systematic review or meta-analysis, and no claim is made that every eligible publication has been captured.

Sources and Search Strategy

For a reproducible update or journal submission, searches should be conducted and recorded in ERIC, Scopus, Web of Science, and relevant publisher databases, supplemented by Google Scholar for citation chaining and official sources such as UNESCO. The search concepts should combine AI terms with learning and resistance terms. Example search strings are: ("artificial intelligence" OR "generative AI" OR ChatGPT OR "intelligent tutoring" OR "adaptive learning") AND ("learning resistance" OR disengagement OR motivation OR engagement OR avoidance); and ("AI in education" OR "adaptive learning system") AND (privacy OR bias OR autonomy OR "mandatory use" OR trust). Searches should record the database, date, exact string, filters, and number of records retrieved.

The present revision draws on the sources cited in the manuscript and additional scholarly and policy literature that could be bibliographically verified. Because a full database export and auditable screening log were not supplied with the original manuscript, this paper does not report invented retrieval totals, duplicate counts, or a PRISMA flow diagram. Before submitting to a journal that requires a systematic or scoping review, the authors should execute the searches, retain the records, document screening decisions, and revise this section to report the actual process.

Eligibility and Selection Principles

For a transparent follow-up search, eligible sources should include peer-reviewed empirical studies, systematic reviews, meta-analyses, established theoretical publications, and authoritative policy reports relevant to AI in education, motivation, engagement, learning barriers, or responsible educational technology. Priority should be given to research published from 2019 through the final search date, while retaining foundational theoretical works where necessary. Sources should be excluded when they lack identifiable authorship or publication details, make unsupported promotional claims, or discuss AI without a meaningful connection to educational processes. English-language restrictions, if applied, should be reported as a limitation rather than left implicit.

Thematic Synthesis

The literature is organised around five dimensions of resistance and four cross-cutting questions: the AI application involved, the proposed mechanism, the nature of the available evidence, and the conditions or risks that qualify the claim. Findings from systematic reviews and meta-analyses are distinguished from conceptual arguments and individual empirical studies. Where studies examine engagement, achievement, attitudes, or technology acceptance rather than learning resistance itself, their relevance is treated as indirect. This distinction prevents the review from claiming that a related outcome is direct proof of reduced resistance.

Methodological Limitations

The review is conceptual and interpretive. It does not estimate an overall effect size, establish causal relationships, or demonstrate that AI reduces learning resistance among all learners. The literature uses varied technologies, populations, measures, and implementation contexts. Direct research on the construct of learning resistance may also be less developed than research on engagement, motivation, achievement, or technology acceptance. These constraints mean that the conclusions should be read as a theoretically informed synthesis and research agenda, not as definitive evidence of universal effectiveness.

AI in Education: Applications and Evidence

Adaptive Learning and Intelligent Tutoring

Adaptive learning environments can adjust content, sequence, hints, or practice in response to learner performance. Intelligent tutoring systems may provide stepwise support, worked examples, and corrective feedback. A meta-analysis by Wang et al. (2024) reported a positive average effect of AI-enabled adaptive learning systems on cognitive learning outcomes, while also identifying moderators across study and implementation characteristics. This finding supports the educational relevance of adaptive systems but does not, by itself, establish an effect on learning resistance. A learner may improve on a task without experiencing less anxiety, greater autonomy, or stronger willingness to participate.

The potential contribution to resistance is indirect: when the level of challenge is better matched to prior knowledge, learners may experience fewer avoidable failures and may be more willing to persist. However, poor adaptation can misclassify learners, narrow the curriculum, or repeatedly assign tasks that are too easy or too difficult. Teachers need access to the reasoning behind recommendations and opportunities to correct inappropriate system decisions.

Generative AI and Conversational Support

Generative AI can provide alternative explanations, examples, summaries, question prompts, and opportunities for iterative dialogue. These features may be particularly useful when learners hesitate to ask a question publicly or need another explanation outside classroom hours. Kasneci et al. (2023) discuss educational opportunities and challenges associated with large language models, including support for learning alongside concerns about reliability, bias, and the need for critical evaluation.

The evidence should nevertheless be interpreted cautiously. Lo et al. (2024), in a systematic review of 72 studies, found that ChatGPT's relationship with student engagement includes both engagement and disengagement outcomes. This mixed picture challenges claims that conversational AI necessarily increases participation. The educational result depends on the task, learner, teacher guidance, quality of generated responses, and whether the tool promotes active thinking or simply supplies answers.

Learning Analytics and Early Support

Learning analytics may help teachers notice patterns such as repeated errors, incomplete tasks, or declining participation. Used carefully, these signals can prompt timely conversations and additional support. They should not be treated as transparent measures of motivation or as proof that a student is resistant. Behavioural traces are context-dependent: a learner may stop logging in because of connectivity problems, shared-device constraints, disability, work responsibilities, or dissatisfaction with the platform. Predictive tools should support professional judgement rather than label learners or determine access to opportunities without review.

Automated Feedback and Assessment

Timely feedback can help learners identify errors while the relevant task remains active. AI-supported feedback may offer repeated practice and explanations at scale, but feedback quality matters more than speed alone. Incorrect, vague, excessively detailed, or discouraging feedback can deepen misconceptions and frustration. Teachers should validate feedback in consequential learning contexts, and students should be taught to compare AI-generated suggestions with course materials, evidence, and disciplinary standards.

How AI May Influence Different Dimensions of Learning Resistance

The following synthesis links AI applications to plausible mechanisms and qualifications. It is a conceptual mapping of the literature rather than a claim that every pathway has been directly tested.

Dimension	Potential AI-supported mechanism	Risks and boundary conditions	Evidence needed
Cognitive	Adaptive sequencing, worked examples, hints, alternative explanations, staged practice.	Incorrect explanations, information overload, weak alignment with prior knowledge, excessive dependence on hints.	Direct measures of perceived difficulty, cognitive load, misconception correction, and transfer.
Emotional	Private question-asking, low-stakes practice, non-judgemental feedback, opportunities to retry.	Unreliable responses, surveillance concerns, impersonal interaction, feedback that increases anxiety.	Repeated measures of anxiety, confidence, perceived safety, and learner accounts.
Behavioural	Reminders, progress feedback, task breakdown, accessible practice opportunities.	Monitoring may feel coercive; activity metrics may reward clicks rather than meaningful participation.	Behavioural observations combined with interviews and validated engagement measures.
Motivational	Meaningful choice, relevant examples, visible progress, support	Compulsory use, gamification without	Measures of autonomous motivation, perceived competence,

	for competence and autonomy.	purpose, reduced agency, extrinsic rewards replacing interest.	autonomy, and persistence.
Sociocultural	Translation support, accessible formats, multiple entry points, differentiated examples.	Digital divide, language or cultural bias, inaccessible design, unequal data protection, exclusion.	Disaggregated outcomes, accessibility audits, equity analysis, and qualitative learner perspectives.

Cognitive Barriers: Matching Challenge with Support

Cognitive resistance may occur when students perceive a task as too difficult, explanations as incomprehensible, or the volume of information as unmanageable. AI can offer a second explanation, divide a complex task into smaller steps, generate examples, or provide hints. These supports may reduce avoidable difficulty and enable learners to re-enter a task. However, a tool should not simply make every task easier. Productive learning sometimes requires effort and uncertainty. The goal is to make challenge manageable while preserving conceptual depth and opportunities for independent problem-solving.

Teachers should therefore use AI-generated scaffolds as temporary supports, check the accuracy of explanations, and gradually withdraw assistance where appropriate. An evaluation should examine not only immediate task completion but also whether learners can explain concepts and transfer understanding to new situations.

Emotional Barriers: Confidence, Anxiety, and Trust

Learners may avoid participation because they fear public mistakes or anticipate negative judgement. A conversational system can provide a private space for rehearsal and repeated questions, which may reduce the social cost of admitting confusion. Yet this benefit is not guaranteed: learners may become frustrated by inconsistent answers or may wrongly assume that an AI system is always authoritative. Emotional safety must therefore be designed through clear expectations, supportive teacher relationships, and explicit permission to question the system.

AI should not be positioned as a substitute for pastoral care or professional support. When emotional distress is significant, automated interaction alone is inadequate. Teachers and institutions must maintain routes for human help and avoid interpreting low activity as evidence of a psychological problem.

Behavioural Barriers: Participation without Surveillance

Task breakdown, reminders, accessible practice, and timely prompts may help students initiate and sustain learning activities. Learning analytics can alert teachers to possible difficulties, but the signal should trigger inquiry rather than punishment. Monitoring becomes counterproductive when learners feel that every action is recorded, compared, or used to label them. Institutions should explain what data are collected, why they are needed, who can access them, and how long they are retained.

Behavioural indicators should also be interpreted alongside context. Non-completion may reflect unclear instructions, insufficient time, device sharing, connectivity problems, or a legitimate objection to the task. A responsible response identifies and addresses barriers rather than automatically increasing reminders or imposing stricter controls.

Motivational Barriers: Autonomy, Relevance, and Competence

Personalised examples and feedback may help learners connect a topic to their interests and recognise progress. In self-determination theory terms, AI may support competence when it offers actionable guidance and autonomy when it enables meaningful choices (Ryan & Deci, 2020). These effects depend on implementation. A system that prescribes every next step or requires constant interaction can reduce

ownership. Likewise, badges and points may encourage short-term activity without cultivating enduring interest.

Teachers can use AI to offer a small set of curriculum-aligned pathways, invite learners to select examples, and ask students to explain why a generated answer is persuasive or flawed. Such use positions AI as a resource for agency and critical judgement, not merely as an answer-producing machine.

Sociocultural Barriers: Access, Language, and Inclusion

AI may provide translation, text simplification, alternative representations, and support for learners who need different routes into a concept. These possibilities are important where classes include varied language backgrounds, prior knowledge, or accessibility needs. Yet AI systems may perform unevenly across languages and communities, while unequal access to devices, connectivity, paid tools, and quiet study space can reproduce existing disadvantage.

Equity cannot be achieved by making a tool available in principle. Institutions need to examine who can use it reliably, whose language and experience are represented, whether outputs are accessible, and whether students are penalised for lacking access. Sociocultural resistance may be a rational response to exclusion or a mismatch between the technology and the learner's context. It should not be reduced to a personal attitude problem.

When AI May Increase Learning Resistance

A balanced review must examine circumstances in which AI is ineffective or counterproductive. First, inaccurate or fabricated outputs can damage trust and create additional work for learners who must detect and correct errors. Second, poorly designed interfaces and excessive information can raise cognitive demands. Third, compulsory use can weaken autonomy, particularly when learners have no meaningful alternative or cannot see the educational purpose. Fourth, opaque profiling and surveillance may make learners feel judged rather than supported. Fifth, unequal access and biased outputs may deepen existing disparities.

Mohd Daud (2026) examines emotional friction and academic decline in enforced AI learning environments, highlighting the relevance of negative technological experiences and mandatory use. This is an important warning, but it should be interpreted in relation to that study's setting and design rather than generalised to every educational context. More broadly, UNESCO (2023) argues for human-centred safeguards, while Kasneci et al. (2023) identify reliability and pedagogical challenges associated with large language models.

Overdependence is another concern. If learners routinely outsource reasoning, writing, or problem-solving, they may complete tasks without developing the knowledge and strategies those tasks are intended to cultivate. The solution is not necessarily to prohibit all AI use; it is to design tasks that make thinking visible, require verification and explanation, and establish transparent boundaries for appropriate assistance. In some situations, non-use or limited use may be pedagogically justified.

These risks show why 'more AI' is not a sufficient intervention. The relevant conditions include technical reliability, clear learning objectives, age-appropriate use, teacher preparation, accessible infrastructure, privacy protection, learner choice where feasible, and ongoing evaluation of unintended effects.

Human-Centred Implementation Framework

A practical implementation framework should connect the educational problem to a justified use of AI and then evaluate whether the intervention improves learning conditions. The following principles are proposed for schools and teacher educators:

1. Begin with the barrier, not the technology. Identify whether the difficulty is conceptual, emotional, motivational, behavioural, social, or related to access before selecting an AI tool.

2. Use AI for bounded pedagogical purposes. Specify what the tool should help learners do, what it should not do, and how its output will be checked.
3. Preserve teacher mediation. Teachers should interpret learner needs, verify important content, support relationships, and intervene when automated recommendations are inappropriate.
4. Make learner agency visible. Where possible, offer meaningful choices, explain why the tool is being used, and allow students to question, verify, or decline unsuitable outputs.
5. Teach AI literacy. Students need practice in checking claims, identifying uncertainty, protecting personal information, and acknowledging assistance according to institutional rules.
6. Protect privacy and equity. Collect only necessary data, communicate data practices, provide accessible alternatives, and avoid disadvantaging students who have weaker connectivity or limited devices.
7. Evaluate outcomes directly. Measure learning resistance alongside achievement, motivation, engagement, confidence, and learner experience; do not treat one outcome as a substitute for all others.

Educational Implications

Implications for Teachers

Teachers require professional development that combines practical AI literacy with pedagogical judgement, critical evaluation, privacy awareness, and inclusive instructional design. Training should not be limited to prompt-writing or tool operation. Teachers need to know when AI is appropriate, how to verify outputs, how to recognise overreliance, and how to interpret learning analytics without labelling students. AI is most useful when it expands the teacher's capacity to respond to learners while leaving relational and professional responsibilities with educators.

Implications for Learners

Students should be encouraged to use AI as a source of support rather than an unquestionable authority. Classroom activities can require students to compare AI explanations with textbooks, identify unsupported claims, revise inaccurate responses, and explain their own reasoning. Such practices can promote epistemic caution and critical thinking. Clear guidance is also needed about privacy, academic integrity, appropriate disclosure, and the limits of AI-generated feedback.

Implications for Institutions and Policymakers

Institutions should establish policies on acceptable use, data protection, age-appropriate access, assessment design, accessibility, and accountability. They should provide equitable access or equivalent alternatives and ensure that vendors' claims are evaluated against educational needs. Policy should avoid both uncritical adoption and blanket assumptions that every AI application is harmful. Decisions should be based on educational value, risk assessment, transparency, and evidence from local implementation.

Implications for Researchers

Researchers should distinguish learning resistance from adjacent constructs and develop measures with evidence of content validity, reliability, and construct validity. Studies should report the specific AI tool, instructional design, duration, teacher role, learner characteristics, access conditions, and comparison group. Mixed-method designs can combine scale scores and behavioural data with interviews that clarify why learners participate or withdraw. Results should be disaggregated where appropriate to examine whether benefits and harms differ by language, disability, socioeconomic context, gender, locality, and prior digital experience.

Future Research Agenda

The most important next step is to test whether AI interventions reduce learning resistance directly, rather than assuming that improved achievement or increased platform activity proves such a reduction. Several research directions follow.

- Construct development: clarify the boundaries and dimensions of learning resistance and test whether the proposed five-dimensional structure is supported empirically.
- Measurement: develop or adapt instruments and establish validity evidence, internal consistency, test–retest reliability where appropriate, and measurement comparability across learner groups.
- Causal evaluation: use well-designed experimental or quasi-experimental studies with baseline measures, suitable comparison conditions, clear intervention descriptions, and follow-up assessments.
- Mechanism testing: examine whether changes in perceived competence, autonomy, cognitive load, feedback quality, trust, or anxiety mediate changes in resistance.
- Longitudinal research: determine whether short-term novelty effects persist and whether repeated AI use strengthens independent learning or increases dependency.
- Equity analysis: investigate differential access, language performance, accessibility, bias, and unintended effects among students from varied educational and socioeconomic backgrounds.
- Implementation research: compare teacher-mediated, learner-directed, optional, and compulsory AI use while documenting classroom climate, professional development, and institutional policy.
- Qualitative inquiry: explore how students explain their willingness or reluctance to use AI, including circumstances in which resistance is a justified response to poor design or coercive implementation.

Future studies should predefine primary outcomes and report null or adverse findings as well as positive results. Researchers should avoid using broad terms such as 'engagement' as a substitute for learning resistance unless the conceptual and measurement relationship is justified. Replication across subjects, age groups, school systems, and language contexts will be necessary before broad claims can be made.

LIMITATIONS OF THE PRESENT REVIEW

This paper offers a conceptual synthesis rather than a systematic review with a complete, reproducible record of database retrieval and screening. The cited literature includes different educational levels and AI applications; findings from higher education or general engagement research cannot automatically be transferred to secondary-school learning resistance. Much of the relevant evidence examines achievement, engagement, motivation, or attitudes rather than resistance as a distinct outcome. The proposed mechanisms and synthesis table should therefore be understood as an organising framework for future testing. A journal submission requiring a systematic or scoping review should be preceded by documented searches, deduplication, screening, full-text eligibility assessment, and a transparent account of excluded records.

CONCLUSION

Artificial intelligence may contribute to reducing learning resistance when it helps learners access appropriately challenging material, receive timely and informative feedback, practise without unnecessary embarrassment, and exercise meaningful agency in the learning process. Adaptive learning, intelligent tutoring, conversational support, and learning analytics offer plausible ways to identify or respond to barriers. However, the current literature does not justify the unconditional claim that AI reduces learning resistance in every context. Evidence about achievement and engagement is relevant but indirect unless resistance itself is measured.

AI can also intensify resistance when it produces unreliable information, overwhelms learners, undermines autonomy, invades privacy, reinforces bias, or is imposed without adequate explanation and support. These risks make teacher mediation and institutional accountability central rather than optional. A human-centred approach treats learners as active participants whose responses provide evidence about the quality of the learning environment, not as problems to be corrected by technology.

The most defensible conclusion is therefore conditional: AI can help create conditions in which learning resistance may diminish, but the outcome depends on pedagogical purpose, technical quality, teacher judgement, learner agency, accessibility, and ethical safeguards. The next stage of research must test these pathways directly, develop robust measures of learning resistance, and examine both beneficial and adverse outcomes across diverse educational contexts.

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