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Review Article

From Algorithmic Control to Learner-Driven Personalisation: Rethinking AI in Education

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Abstract - AI-driven personalised learning now shapes the pace, practice, and feedback of millions of learners. Most systems, however, personalise learning for the learner through opaque algorithmic decisions instead of equipping learners to personalise their own study. This review examines that asymmetry. Twenty-five studies published between 2017 and 2026, retrieved from Google Scholar, ERIC, and Scopus, are synthesised thematically around learner agency, self-regulated learning, and system design. The synthesis identifies an illusion of autonomy: surface-level choices sit alongside algorithmic authority over goals, sequencing, and mastery criteria, which narrows the room learners have to practise goal setting, strategic monitoring, and reflective evaluation. Duolingo and two platforms used in Vietnam serve as illustrative cases showing how gamified metrics and default pathways can redirect attention from meaningful goals towards externally driven engagement. The paper answers with a learner-driven personalisation framework resting on three principles: shared control, design that activates self-regulated learning, and algorithmic transparency coupled with AI literacy. A three-item rubric operationalises the framework so that schools can detect illusion-of-autonomy risks before adoption. The analysis extends to equity, since learners with limited devices, connectivity, or AI literacy gain the least from transparency measures that presuppose digital capital. Implications concern system designers, educational leaders, and teachers in Vietnam, who need evaluation criteria reaching beyond short-term performance. The contribution is a concise screening tool that links learner control, the three phases of self-regulated learning, and algorithmic transparency, complementing broader agency rubrics with a focused test for illusion-of-autonomy risks.

Keywords - Adaptive Learning Platforms, Educational Equity, Learner Agency, Self-Regulated Learning, Shared Control.

1. Introduction

Online platforms, intelligent tutoring systems, and learning analytics have turned personalised learning into an ordinary feature of education over the past decade. Instead of one path for everyone, these systems read behaviour, performance, and pace, and then recommend what a learner should do next. In theory, the idea connects to learner-centredness: respect individual differences, help learners understand how they learn, and let them take ownership of their study [1]. In practice it rests on machine-learning models that automate task selection, content sequencing, and the timing of feedback [2, 3].

Institutions find the proposition attractive for two reasons at once. Classes vary widely in proficiency, and teacher capacity is finite. Personalisation promises a better fit for each learner, together with an automated share of progress monitoring. That promise holds only when personalisation leaves intact the competencies education exists to build, above all, independent learning and critical thinking [4].

A paradox has surfaced alongside the growth. Many systems personalise for the learner on the basis of algorithmic decisions, while the learner receives outputs and takes almost no part in the decision itself. Bernacki et al. [4] frame personalised by whom as the pivotal question in this body of work. Where goals, competency standards, mastery criteria, and activity sequences are fixed by the algorithm, personalisation can raise short-term scores and still erode the capacity for self-directed study over a longer horizon.

Learner autonomy is tied closely to Self-Regulated Learning (SRL). Zimmerman [5] describes SRL as a cycle in which learners direct their own cognition, behaviour, and motivation across three phases: forethought, covering goal setting and planning; performance, covering self-monitoring and strategy adjustment; and self-reflection, covering self-evaluation and the drawing of lessons. On this account, personalisation is authentic when it develops these processes instead of substituting for them [6-8]. Evidence from digital environments supports the claim. Goal setting and strategic planning predict goal attainment in massive open online courses [9].

Terminology in this field is used loosely, and the looseness hides real disagreement. Table 1, therefore, fixes the working definitions adopted throughout the paper before the argument proceeds.

Table 1. Working definitions of the key constructs used in this review

Construct	Working definition adopted in this review	Anchor sources
Personalised learning	Adaptation of goals, content, methods, and assessment to the needs, abilities, and context of an individual learner.	[4, 10]
Learner agency	The capacity of a learner to form intentions, act on them, and reflexively shape the conditions under which learning takes place.	[11, 12]
Learner control	The share of instructional decisions, spanning goal, task, difficulty, sequence, and mastery criterion, that the learner is permitted to make.	[13, 14]
Self-regulated learning	The cyclical process through which learners set goals, monitor and adjust strategy, and evaluate outcomes across three phases.	[5, 8]
Algorithmic control	The condition in which a system's models determine instructional decisions, while the learner cannot see, contest, or override them.	[15, 16]
Illusion of autonomy	The experience of choosing freely while the decisions that matter remain fixed inside the system frame.	[17, 18]

Three gaps follow from this literature. Reviews of personalised learning document the by-whom problem thoroughly but do not consistently translate it into SRL-linked design requirements [4, 10]. Research on learner agency in adaptive technologies has begun to operationalise agency through comprehensive frameworks and rubrics, notably the LADA model and AiPAL rubric [19], but a short screening tool focused specifically on illusion-of-autonomy risks remains underdeveloped.

The empirical base is also concentrated in Western higher education, whereas deployment in Vietnam is proceeding without a shared pedagogical evaluation framework [20, 21]. This review addresses the first and third gaps directly and offers a focused complement to existing agency instruments. Three questions organise the paper. First, how does recent literature describe the paradox in which an algorithm decides on the learner's behalf? Second, what does this paradox do to learner agency and self-regulated learning capacity? Third, which design principles would move a system from algorithmic control towards learner-driven personalisation?

The contribution is threefold. The paper converts the by-whom problem into three design principles linked to the phases of self-regulated learning, supplies a concise three-item screening rubric that schools and teachers can apply to a candidate platform before adoption, and situates both in the Vietnamese deployment context, including the equity consequences for learners with limited devices, connectivity, or AI literacy.

2. Materials and Methods

This study combines a purposive literature review with conceptual analysis. Four steps structure the work: defining the review questions and the analytical framework; searching databases and scholarly sources; screening, coding, and synthesising the evidence; and constructing the proposed framework together with its implications.

Searches were run on Google Scholar, ERIC, and Scopus, with the final search completed in May 2026. Core keyword clusters combined personalised learning with learner agency, self-regulated learning, learner control, algorithmic control, and adaptive learning platform.

Vietnamese-language equivalents were searched separately in the Vietnam Journal of Educational Sciences and on Google Scholar using the phrases học tập cá nhân hóa, tự chủ người học, and tự điều chỉnh trong học tập. For the case illustrations, targeted searches also combined Duolingo, VioEdu, and ELSA Speak with learner agency, autonomy, self-regulated learning, and personalisation.

2.1. Inclusion and Exclusion Criteria

A record was included when it satisfied all four of the following conditions: published between 2017 and 2026, or published earlier where the work is foundational to theories of self-regulation, motivation, or agency; issued as a peer-reviewed journal article, an edited book chapter, a systematic review, or an institutional report from a recognised body; written in English or Vietnamese; and addressing the relationship between personalisation, learner control, agency, or self-regulation within an educational setting.

Because the review concerns the pedagogical and psychological dimension of personalisation rather than its engineering, four exclusion criteria were applied at the full-text stage. Excluded were purely technical works reporting model or algorithm accuracy without any discussion of learner behaviour or capacity; studies of personalisation in non-educational domains such as healthcare or e-commerce with no clear pedagogical application; general EdTech overviews too broad to speak to the relationship between personalisation and agency; and studies measuring only short-term outcomes such as test results or completion rates with no indicator of agency or self-regulation.

Screening proceeded in three rounds. Titles and abstracts were read first to remove off-topic material, full texts were then assessed against the inclusion criteria, and the retained records were coded against the analytical framework.

The initial search returned 180 records; 60 were read in full; and 25 met the inclusion criteria and entered the thematic synthesis, of which five are Vietnamese-language sources. Figure 1 summarises the process. The 25-study synthesis pool covers 2017-2026; earlier foundational works were used for theoretical framing and were not counted in the flow. Screening and coding were carried out by the author team, and disagreements were resolved by discussion until consensus was reached.

Additional contextual sources were cited outside the synthesis pool to support the treatment of AI literacy, explainable AI, and learning analytics. This procedure does not comply fully with the PRISMA protocol and is best described as a purposive review rather than a comprehensive systematic review.

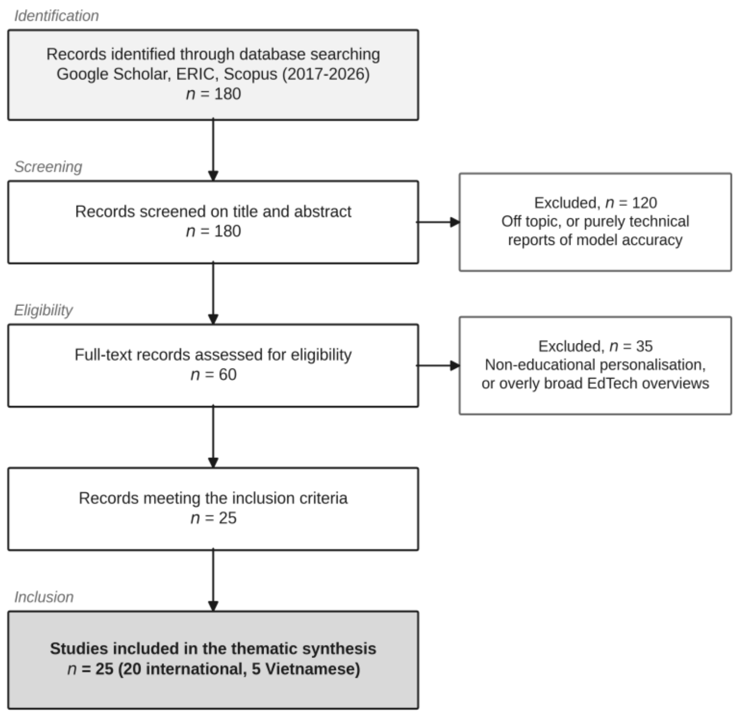

Fig. 1 Identification and screening of records included in the thematic synthesis

2.2. Synthesis and Case Selection

Analysis followed a thematic synthesis approach. Each document was read in full and recorded against a common extraction template covering study type and context; the degree of learner control, classified into the three levels set out in Section 3.1; feedback mechanisms and the role of gamification; the degree of support offered to each of the three SRL phases; and algorithmic transparency together with AI literacy. Extraction notes were coded into five corresponding thematic groups and cross-referenced across documents to identify convergent findings, divergences, and disconfirming evidence. The synthesised concepts then informed the construction of the proposed framework.

Three platforms were selected as illustrative cases rather than as a representative sample. Duolingo was chosen as a typical case because it is documented in the peer-reviewed literature and its personalisation mechanics are publicly described. VioEdu and ELSA Speak were added as contextual cases because their public-facing descriptions foreground AI-based recommendation and both are used in Vietnam. The case analysis draws on publicly available feature descriptions and on the scholarly literature identified by the targeted searches. Its purpose is not to generalise to all platforms but to make the mechanism of the paradox observable in recognisable settings.

3. Results

3.1. Personalised Learning and the Question of By Whom

Personalised learning is generally understood as the adaptation of goals, content, methods, and assessment to the needs, abilities, and context of each learner. Definitions and implementation approaches differ enough, however, to produce very different degrees of personalisation in practice. Bernacki et al. [4] contribute a systematic framework of four guiding questions: personalised by whom, against what standard, by what means, and for what purpose. The first of these settles the educational philosophy of a system. Where the learner is the decision-making agent, perhaps supported by a teacher and a set of tools, personalisation aims at building capacity. Where the algorithm is the agent, personalisation risks collapsing into performance optimisation [10]. Research on learner control long predates the current wave of AI. Corbalan et al. [13] showed that shared task selection, in which system and learner negotiate the next task, produced better outcomes than either full system control or full learner control. Scheiter and Gerjets [14] reached a similar conclusion for hypermedia environments, adding that control benefits learners only when they possess the metacognitive skill to exercise it. Both findings matter for the present argument. Control is not valuable in itself; it is valuable when paired with the capacity to use it, and that capacity has to be built deliberately. Three levels of learner control can be distinguished on this basis, and they map unevenly onto the SRL phases. Table 2 sets out the levels, and Figure 2 shows the phases each level most directly activates; the arrows are not exclusive, and level 3 still presupposes strategic monitoring during performance. Many current systems do not advance beyond level 1 or part of level 2, while level 3 provides the strongest opportunity for long-term autonomy to develop.

Table 2. Three levels of learner control in AI-based personalisation

Level	Decisions held by the learner	Decisions retained by the system	Typical platform feature	SRL phase activated
1. Surface choice	Session length, broad topic, reminder settings	Goals, sequence, difficulty, mastery criteria	Daily goal slider, topic picker, streak reminder	None in any sustained way
2. Strategic choice	Task type, difficulty, order of practice	Goals and mastery criteria	Practice mode selector, difficulty toggle, test-out option	Performance
3. Goal and criterion control	Objectives, evidence of mastery, revision of the plan	Candidate options and the rationale offered for each	Learner-defined objectives, negotiable mastery thresholds, editable study plan	Forethought and self-reflection

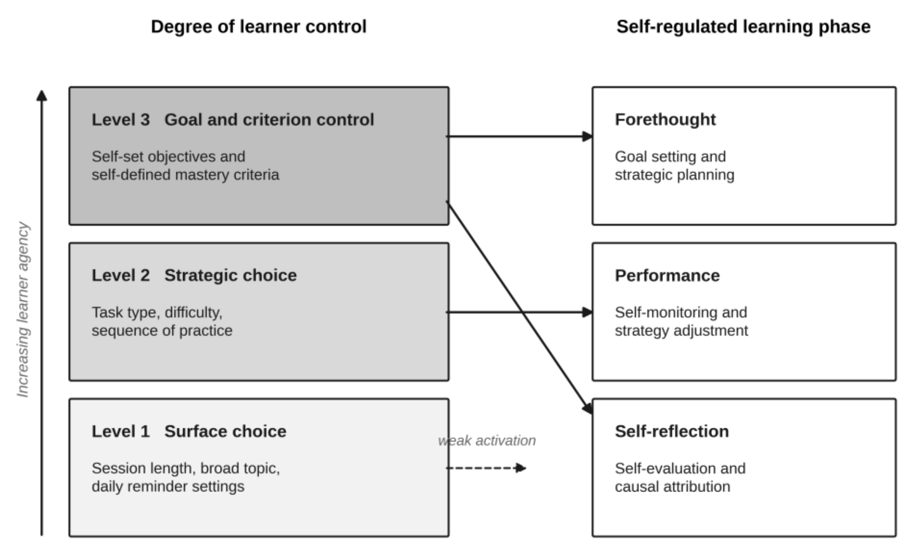

Fig. 2 Mapping of the three levels of learner control onto the phases of self-regulated learning

In practice, many AI-based personalisation systems run on an automation model: the system analyses data, predicts needs, and decides the next activity. Speed and scalability follow. So does the risk of positioning learners as users of a path rather than builders of one. Brass and Lynch [23] argue that the history of personalised learning is bound up with successive waves of technology reform in which technology was expected to solve quality problems without anyone addressing the underlying pedagogical ones.

Evaluating a personalised system, therefore, cannot rest on score gains or engagement metrics alone. It requires an assessment of the autonomy the system creates. Can learners set goals that reflect their own needs? Can they choose strategies and monitor their own progress? Is there any mechanism that helps them reflect on a plan and revise it? These questions lead directly into the SRL framework taken up in the next section.

In Vietnam, the by-whom question is especially pressing because AI learning platforms are being deployed widely without an adequate pedagogical evaluation framework. Bui et al. [20] note that adaptive education models for Vietnam need design criteria drawn from learner capacity, such as degree of autonomy and self-regulation, and not only from technical performance, such as recommendation accuracy and response speed. An and Ngo [21], studying Vietnamese university students on AI-enabled platforms, found that adaptive features can improve short-term outcomes while learner self-efficacy remains the strongest moderating variable. Higher-order control, meaning the power to set one's own goals and criteria, therefore deserves greater priority if results are to last.

3.2. The Illusion of Autonomy in AI-based Personalisation

A prominent theme in recent literature is the illusion of autonomy. Learners are offered surface-level choices such as pace, a daily target, or a general topic, while the algorithm keeps decision-making authority over the learning path and the mastery standards. Learners feel they are directing themselves. They are, in fact, following a behavioural-optimisation script derived from historical data. Where choices exist only inside a frame the system defines, autonomy shrinks into a usage operation [17, 18].

Yeung [16] gives this arrangement a name that travels beyond education. A hypernudge is a dynamic, data-driven choice architecture that steers behaviour by continually reconfiguring the options presented, without the person noticing that the configuration has changed. Streak mechanics, adaptive difficulty, and personalised reminders fit the description precisely. Williamson [15] adds the institutional layer: once learning is governed through data infrastructures, the criteria of educational success migrate quietly into the design decisions of platform vendors. Selwyn [24] presses the same point for learning analytics, cautioning that what gets measured becomes what counts as learning.

The paradox becomes sharpest when set against the SRL model. In the forethought phase, learners need to form personally meaningful goals and strategic plans. If goals are replaced by system-defined targets such as maintaining a streak, earning engagement points, or completing tasks in a fixed order, learners lose both intrinsic commitment and the chance to practise goal setting. Self-determination theory predicts exactly this outcome, since externally regulated targets undermine the experience of volition that sustains engagement over time [22, 25].

During the performance phase, learners must monitor themselves and adjust strategy when difficulty rises; a system that always steers the next step and delivers immediate right or wrong feedback removes the felt need to think strategically. In the self-reflection phase, learners need to evaluate outcomes and interpret the causes of success or failure; a system that analyses the data on its own and selects the next task hands over the next exercise without inviting the learner into that analysis.

The illusion of autonomy is also associated with reduced transfer. Learners may improve inside a heavily scaffolded environment and then struggle on a new task or in a different context, because they never acquired the self-regulatory strategies the scaffold was supplying. AI-based personalisation, therefore, has to be judged not only on immediate outcomes but on how well it equips learners to study without it.

The paradox is more than a design mistake. Section 3.2.1 sets out what happens to learners who work in algorithm-dominant environments, and Section 3.2.2 examines the structural conditions that keep producing such designs.

3.2.1. Consequences: Algorithm Dependency and the Erosion of Critical Thinking

The direct consequence of a system-decides, learner-complies design is algorithm dependency. Learners come to expect the system to indicate what to study next and where the error lies, which lowers their initiative to seek information, formulate questions, and verify answers on their own. Faced with a new problem, they wait for a prompt instead of analysing the situation and testing a strategy. In environments built around generative AI, dependency can also appear as uncritical acceptance of machine-generated answers, which weakens independent reasoning [26].

Research on help-seeking clarifies the mechanism. Aleven et al. [27] distinguish executive help-seeking, in which a learner asks for the answer, from instrumental help-seeking, in which a learner asks for what is needed to reach the answer alone. Systems that volunteer the next step convert every episode into the executive form and remove the occasion for the instrumental one. The habit generalises. Algorithm dependency undermines critical thinking in two further ways. Learners rarely see the decision process, meaning which data produced which recommendation, so they have little material from which to build the ability to question it. And when feedback arrives packaged as a score or a binary judgement, learners optimise for points rather than for understanding. Both consequences point towards feedback designs that are informative and that call for explanation and reflection.

3.2.2. Root Causes: Why Technical Optimisation and Pedagogical Goals Diverge

The illusion of autonomy usually originates in a misalignment between technical optimisation and pedagogical goals. On the technical side, systems optimise objectives that are easy to measure, such as reduced dropout, longer usage time, or higher test scores. Autonomy, self-regulation, and critical thinking are hard to measure and mature slowly. When short-term metrics drive development, design choices tilt towards automation rather than empowerment [28]. Gašević et al. [30] made the parallel argument for learning analytics: analytics deliver value only when their measures are grounded in a theory of learning rather than in whatever the log files happen to record.

An interdisciplinary gap compounds the problem. Technical and educational teams lack a shared language, and where learning theory is not translated into concrete design requirements, algorithms tend to absorb the cognitively demanding steps of goal setting, planning, and self-evaluation in order to reduce friction in the user experience. Yet calibrated cognitive friction is precisely the condition under which learners mature strategically. Bjork and Bjork [29] describe such conditions as desirable difficulties: they slow immediate performance and improve durable learning. A design philosophy dedicated to removing friction will systematically remove them.

3.3. Case Illustrations: Duolingo and Two Platforms Used in Vietnam

Duolingo is a popular language-learning platform discussed frequently in connection with AI-based personalisation. The system uses practice data to adjust exercise difficulty and to recommend the next task, which can help learners sustain a short daily habit. Independent studies complicate the picture. Cárdenas et al. [31] identify pedagogical constraints when Duolingo is used within formal instruction and argue that curriculum integration requires teacher mediation.

In a mixed-methods study, Saniyah [32] found that learners valued translation, speaking, and listening features, but often framed goals through daily scores and leaderboard positions rather than through explicit language-mastery criteria. Verghis et al. [18], in a conceptual opinion article, argue that a choice limited to a system-defined frame may not amount to substantive autonomy.

Many gamification features exist to build the habit of opening the application and to sustain engagement. The purpose of SRL is different: to develop the capacity to set personally meaningful goals, monitor strategy, and reflect on outcomes. When extrinsic rewards become substitute goals, learners may study consistently without studying purposefully. Optimising engagement is not the same as optimising learning, and this is a clear illustration of the difference.

Drawing on Zimmerman's [5] SRL framework, the main bottlenecks of Duolingo can be described across the three phases as shown in Table 3.

Table 3. Illustrative matrix of the limitations of Duolingo in supporting self-regulated learning

Phase	Design features	Implications for learner agency
Forethought	Learning goals are reduced to daily duration targets or streak counts; no tool for articulating specific linguistic objectives or personalising a study plan.	Reduced opportunity for personally meaningful goal setting; the illusion of autonomy arises because choice exists only at the surface level.
Performance	Immediate feedback and gamification mechanics such as experience points, leaderboards, and rewards orient behaviour towards extrinsic goals; default pathways minimise the need for strategic choice.	Extrinsic motivation rises while strategic self-monitoring is displaced; dependency on the system to sustain learning behaviour becomes a risk.
Self-reflection	The system aggregates progress and selects the next task on its own; learners receive suggestions without being asked to explain error patterns or revise their plans.	Self-evaluation and reflection stay underdeveloped; learners struggle to convert feedback data into independent learning strategies.

The illustration suggests that Duolingo can support practice habits and foundational knowledge, while evidence about higher-order self-regulation remains limited. Gamal et al. [33] reported significant gains in EFL writing after eight weeks of supplementary Duolingo use, but their study did not measure learner agency, self-regulated learning, or delayed outcomes.

Ma and Chen [34], in a 16-week three-group study, found that AI combined with teacher scaffolding produced stronger and more sustained proficiency gains than AI alone or non-AI gamified activities; their qualitative findings also linked scaffolding to a shift towards self-regulated learning. Together, these studies suggest that app-based practice can improve performance, while the development of self-direction depends on how the tool is pedagogically mediated.

VioEdu and ELSA Speak provide contextual illustrations of the same question in Vietnam. Their publicly described functions emphasise system-generated recommendations, progress indicators, pronunciation scores, and prescribed practice. These features may support efficient practice, yet the learner's role in setting objectives, defining mastery, and negotiating sequence is not clearly documented. Within the databases and targeted search strings used in this review, no peer-reviewed study was identified that directly measured the effects of either platform on learner agency or self-regulated learning. This evidence gap, rather than a definitive judgement on the platforms, motivates the research agenda in Section 4.1.

More fundamentally, these cases illustrate the central paradox. The system personalises the next exercise for the learner, yet the learner is never invited into the rationale for that personalisation and holds no right to negotiate or refuse the recommendation. When personalisation happens behind the screen, learners lose the occasions on which they might have learned to make data-informed decisions about their own study.

On the available evidence, the three platforms are most defensible as supplementary practice tools rather than as complete environments for developing autonomous learning. Developing autonomous capacity requires an environment in which learners set goals according to their own purposes, design or revise a plan, and reflect on evidence. Technology supports this development when it makes data transparent and widens the learner's decision-making authority.

3.4. A Learner-Driven Personalisation Framework

Drawing the themes together, this study proposes a learner-driven personalisation framework built on a single shift: AI moves from deciding the pathway to supporting the decision. Three principles constitute the framework, and Figure 3 shows how they reinforce one another.

The first principle is shared control. Rather than a single default path, the system should offer meaningful options, such as a priority skill, a level of challenge, or a type of activity, each accompanied by an explanation of why it is recommended. Final authority rests with the learner, or with the learner together with a teacher, and learners can adjust or annotate their choices so that the system learns from them. Concrete realisations include context-customisable goals, multi-option rather than single-option recommendations, and a mechanism through which learners rate the relevance of a suggestion. The design intent matches the shared-control condition that Corbalan et al. [13] found superior to either extreme.

The second principle is a design that activates self-regulated learning. The system should not perform learners' cognitive steps but prompt learners to perform them. Learners articulate goals, select strategies, predict the difficulty of an item, record progress, and explain the source of an error before full feedback appears. AI supplies prompts, open questions, and information-rich feedback that deepens reflection. Instead of flagging an answer as wrong, for example, the system can present an error pattern, offer several correction strategies, and ask the learner to choose. Azevedo and Hadwin [36] set out the design logic for such metacognitive scaffolds, including the requirement that scaffolds fade as competence grows.

The third principle is algorithmic transparency linked to AI literacy. Learners need to know what data are collected, which criteria generate a recommendation, and where the system's limits lie. Transparency here is not the display of information alone but the building of capacity: knowing when to trust a recommendation, when to verify it, and when to reject it. Kay [35] argued two decades ago that adaptive systems should be scrutable, meaning that the learner model is open to inspection and correction by the learner.

Explainable AI in education and human-centred learning analytics extend the argument, insisting that explanations be meaningful to learners and teachers rather than merely accurate to engineers [38, 39]. Meaning, in turn, depends on competence, which is why AI literacy belongs inside the principle and not beside it [40, 41]. UNESCO [37] frames the same requirement at the policy level.

The three principles form a developmental loop. Shared control creates room to practise self-regulation; as self-regulatory capacity grows, learners make better choices; and transparency makes those choices informed rather than dependent. Personalisation then moves towards sustained effectiveness instead of short-term gain.

Positioning the framework against existing work clarifies its scope. Table 4 shows that the proposal does not replace comprehensive agency models or explainability frameworks. Its narrower contribution is to integrate three elements often treated separately: decision authority, the three phases of self-regulated learning, and learner-facing transparency. The resulting rubric is intentionally brief and is intended for preliminary screening, whereas comprehensive instruments such as AiPAL [19] support a fuller evaluation.

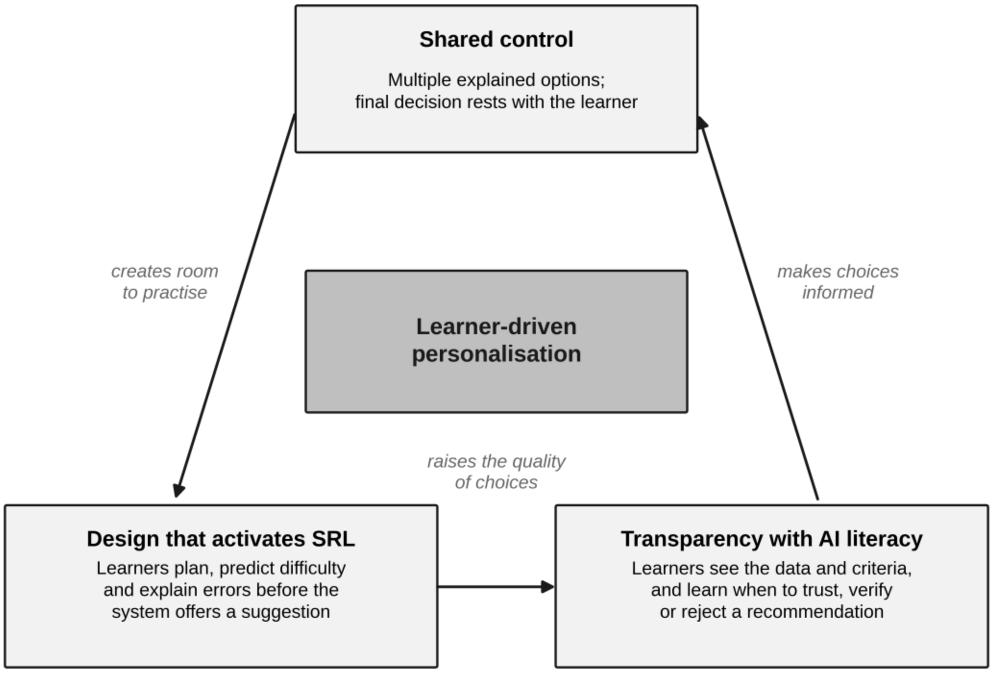

Fig. 3 The learner-driven personalisation framework and its developmental loop

Table 4. Position of the proposed framework relative to existing research

Prior work	What it establishes	What it leaves unspecified	How this review extends it
Bernacki et al. [4]	A systematic question set for personalised learning: by whom, to what standard, by what means, for what purpose.	No design response to the by-whom problem; the question is posed but not answered.	Converts the by-whom question into three design principles that can be built into a system.
Shemshack and Spector [10]	A map of definitional inconsistency across the personalised learning literature.	Agency is not treated as a design variable, and control is not operationalised.	Fixes working definitions (Table 1) and ties them to three measurable levels of learner control (Table 2).
Verghis et al. [18]	A conceptual critique arguing that choice inside a system-defined frame may not constitute substantive autonomy.	The opinion article remains diagnostic and offers no operational threshold for adequate learner control.	Defines goal and criterion control as a proposed operational threshold that still requires empirical validation.
Alrawashdeh and Castillo [19]	The LADA model and a 29-item AiPAL rubric that translates agency principles into observable criteria across personalised and adaptive learning systems.	The rubric is comprehensive rather than a short SRL-phase screen focused specifically on illusion-of-autonomy risks.	Offers a concise pre-adoption screen that complements AiPAL by linking learner control to forethought, performance, and self-reflection.
Khosravi et al. [39]	Requirements for explanations in education that are	Explanation is treated separately from the	Couples transparency with shared control and AI

	meaningful rather than merely accurate.	distribution of decision authority.	literacy inside one developmental loop.
This review	Three SRL-linked design principles, a concise pre-adoption screening rubric, and an application to the Vietnamese deployment context.	The framework has not yet been validated empirically in classrooms.	Section 4.4 sets out the validation programme this requires.

3.5. Quick-Evaluation Criteria Aligned with the Framework

To support practical selection and evaluation of platforms, Table 5 sets out a minimal rubric aligned with the three principles. The rubric does not replace comprehensive evaluation instruments. Its purpose is narrower and more immediate: to help schools and teachers detect illusion-of-autonomy risks early, using evidence that can be gathered from a trial account in a single session.

Table 5. Minimal rubric for evaluating a personalisation platform from a learner-driven perspective

Principle	Checklist question	Risk indicator
Shared control	Can learners set specific goals and modify their own learning path? Does the system offer several options together with the reasons behind each?	Only duration-based goals are available; default paths are effectively fixed; no override or customisation function exists.
Design that activates SRL	Does the system require learners to plan, predict difficulty, and explain errors before it offers a suggestion? Is a strategy journal or reflection tool available?	Feedback is limited to right and wrong; the system determines every next step; no reflection activity is required at any point.
Transparency and AI literacy	Does the system explain the data and criteria behind its personalisation? Do learners learn how to verify a suggestion and recognise the system's limits?	Recommendations are presented as a black box; no explanation is offered; learners are likely to accept suggestions without checking them.

4. Discussion

The framework raises a practical question. Can current AI platforms implement it, and where does deployment in Vietnam stand in relation to it? Four issues left unresolved in the Results are taken up here.

4.1. The Gap Between International Evidence and Vietnamese Practice

Most evidence on the benefits of shared control and SRL activation comes from research conducted in Western settings [19, 26]. In Vietnam, the paradox is relevant to platforms that rely heavily on system-generated recommendations. VioEdu and ELSA Speak, together with default-pathway test-preparation applications and tutoring systems, illustrate this design tendency, although platform-specific evidence on long-term learner agency remains limited. An and Ngo [21] show that adaptive features influence short-term outcomes through perceived value and trust, but their design does not measure long-term self-regulation. Ouyang [42] finds that self-regulated learning and engagement mediate the relationship between adaptive-platform characteristics and educational quality, indicating that immediate outcomes alone provide an incomplete basis for evaluation.

A specific research gap follows. Studies in Vietnam need to measure what AI personalisation does to autonomy and self-regulation over time, and not only what it does to scores and completion rates. Validated Vietnamese-language instruments designed for this specific purpose were not identified in the present search, making instrument development an important next step.

4.2. Enabling Conditions for the Framework in the Vietnamese Context

The framework presupposes three conditions. Learners need sufficient digital competence and AI literacy to understand and question a recommendation. Teachers need training in coaching self-regulation, not only in operating a tool. Administrators need to apply pedagogical criteria alongside technical ones when selecting a platform. UNESCO [37] and Ng et al. [40] both emphasise that guidance on AI in education must be learner-centred and must protect learner autonomy, and that principle still requires operationalisation in Vietnamese policy instruments.

Evidence that all three enabling conditions are satisfied at scale remains limited, which suggests a sequencing implication. Introducing level-3 control into a system whose users lack the metacognitive skill to exercise it will not by itself produce autonomy, as Scheiter and Gerjets [14] warned. The rubric in Table 5 is therefore best used alongside a programme of teacher preparation rather than as a standalone procurement checklist.

4.3. Equity and Marginalised Learners

Discussion of learner agency tends to assume a learner with a device, a stable connection, and enough prior digital experience to make transparency useful. That assumption does not hold everywhere, and where it fails, the framework's own principles can widen the gap they were meant to close.

Three mechanisms deserve attention. The first is access. Household connectivity and device ownership remain unevenly distributed, with rural households and lower-income families least well served [48]. A learner who studies on a shared phone in short bursts is structurally pushed towards level-1 control, because planning and reflection features assume time and screen space that the learner does not have. The second is representation in the model itself. Recommendation and assessment models trained predominantly on majority-group data can misestimate the performance of underrepresented groups, and in education, such misestimation is consequential: a system that reads a second-language learner's slower response as lower ability may route that learner to easier material and reinforce its own prediction. Baker and Hawn [43] document this class of bias across educational applications. In Vietnam, this risk is especially relevant to ethnic-minority learners studying through Vietnamese as an additional language, whose linguistic profiles may be under-represented in model-development data.

The third mechanism is the distribution of AI literacy itself. Transparency delivers value in proportion to a learner's capacity to interpret what is disclosed. Learners who already possess digital capital gain most from an explanation interface; learners who possess least gain least. A transparency requirement introduced without an accompanying literacy programme is therefore regressive in its effects, however progressive in its intent. The same asymmetry applies to teachers: schools with stronger professional development capacity will exploit shared-control features that schools without it cannot.

Ethical frameworks for AI in education increasingly treat these questions as central rather than peripheral [44]. Prinsloo and Slade [45], [46] argue further that institutions collecting learning data incur an obligation to act on what those data reveal, and that failing to act is an ethical position rather than a neutral one. Applied here, the obligation runs in a particular direction: a platform that can identify which learners are stuck at level-1 control has thereby acquired a duty to report it, not merely to optimise around it.

UNESCO's global monitoring of educational technology reaches a compatible conclusion in asking on whose term’s technology enters a classroom [47]. Three implications follow for the framework. Equity criteria belong in the rubric alongside pedagogical ones; AI literacy provision must be funded as part of adoption rather than assumed; and evaluation of any platform should disaggregate outcomes by connectivity, language background, and school resourcing rather than reporting aggregate gains.

4.4. Limitations and Directions for Future Research

Four limitations qualify the conclusions. The literature pool is bounded by database access and search terms, and Vietnamese-language sources that have not been digitised may have been missed. The case illustrations cover three platforms and do not represent the field. The proposed framework has not been validated empirically in any classroom. And the review is purposive rather than systematic, so the synthesis reflects analytic judgement at the coding stage in a way that a PRISMA-compliant procedure would constrain more tightly.

Four lines of work follow. Instruments measuring autonomy and self-regulation in digital environments need to be developed and validated for the Vietnamese context. Comparative trials should test algorithmically controlled designs against learner-driven designs on delayed as well as immediate outcomes, since the arguments advanced here concern durability. The rubric in Table 5 requires validation for inter-rater reliability across schools before it can be recommended for procurement decisions. And equity-disaggregated evaluation should become standard practice rather than an optional extension, given the mechanisms set out in Section 4.3. Reviews of AI-supported self-regulation continue to identify the same absence of longitudinal evidence [17], which suggests the priority is a matter of study design rather than of further conceptual work.

5. Conclusion

AI-driven personalised learning promises efficiency and scale. It also raises a question about agency that the promise does not answer: personalisation can occur for the learner without empowering the learner. This review shows that where algorithms dominate decision-making, an illusion of autonomy and a habit of algorithm dependency can erode self-regulated learning, which is the foundation on which durable learning rests.

The study proposes a learner-driven personalisation framework built on shared control, a design that activates self-regulated learning, and algorithmic transparency coupled with AI literacy, together with a three-item rubric that turns the framework into a preliminary screening procedure schools can use before adoption. The implications are concrete. System design should prioritise learner capacity over engagement metrics. Educational management should judge technology by pedagogical criteria and should disaggregate results by connectivity, language background, and school resourcing. Teachers should be prepared and resourced for a coaching role in digital environments. Realising the framework in Vietnam will require validated instruments and empirical trials, so that AI serves the development of learner capacity rather than substituting for it.

Data Availability

This is a literature review and conceptual study. No primary datasets were generated or analysed. All sources used are cited in the reference list, and the extraction template applied during the synthesis is available from the corresponding author on reasonable request.

Declaration on the Use of Generative AI

During the preparation of this manuscript, the authors used a large language model to assist with sentence-level language editing and paragraph restructuring in English. The tool generated no scholarly content, no argument, and no citation. The authors reviewed and edited all output and take full responsibility for the content, argumentation, citations, and accuracy of the manuscript.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper. The platforms discussed as case illustrations were selected on the basis of documentation available in the public domain, and no author holds any financial or advisory relationship with the organisations that operate them.

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Authors' Contributions

Conceptualisation, M.P., D.T.L. and V.T.P.; Methodology, V.T.P.; Investigation and literature search, M.P., D.T.L. and V.T.P.; Formal analysis and data synthesis, M.P. and V.T.P.; Visualisation, M.P.; Writing – original draft preparation, M.P. and V.T.P.; Writing – review and editing, M.P., D.T.L. and V.T.P.; Supervision, V.T.P. All authors have read and approved the final manuscript.

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References

[1] Tran Thi Thu Huong, "Personalized Learning: Essential Components and Implementation Notes," *Vietnam Journal of Educational Sciences*, vol. 2, no. 2, pp. 1-7, 2022. [Publisher Link]

[2] Ido Roll, and Ruth Wylie, "Evolution and Revolution in Artificial Intelligence in Education," *International Journal of Artificial Intelligence in Education*, vol. 26, no. 2, pp. 582-599, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[3] Olaf Zawacki-Richter et al., "Systematic Review of Research on Artificial Intelligence Applications in Higher Education-where are the Educators?," *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, pp. 1-27, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[4] Matthew L. Bernacki, Meghan J. Greene, and Nikki G. Lobczowski, "A Systematic Review of Research on Personalized Learning: Personalized by whom, to what, How, and for what Purpose(s)?," *Educational Psychology Review*, vol. 33, no. 4, pp. 1675-1715, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[5] Barry J. Zimmerman, "Becoming A Self-Regulated Learner: An Overview," *Theory into Practice*, vol. 41, no. 2, pp. 64-70, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[6] Philip H. Winne, and Allyson F. Hadwin, *Studying as Self-Regulated Learning*, 1st ed., Routledge, 1998. [Publisher Link]

[7] Paul R. Pintrich, *The Role of Goal Orientation in Self-Regulated Learning*, Handbook of Self-Regulation, pp. 451-502, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[8] Ernesto Panadero, "A Review of Self-Regulated Learning: Six Models and Four Directions for Research," *Frontiers in Psychology*, vol. 8, pp. 1-28, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[9] René F. Kizilcec, Mar Pérez-Sanagustín, and Jorge J. Maldonado, "Self-Regulated Learning Strategies Predict Learner Behavior and Goal Attainment in Massive Open Online Courses," *Computers and Education*, vol. 104, pp. 18-33, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[10] Atikah Shemshack, and Jonathan Michael Spector, "A Systematic Literature Review of Personalized Learning Terms," *Smart Learning Environments*, vol. 7, no. 1, pp. 1-20, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[11] Albert Bandura, "Social Cognitive Theory: An Agentic Perspective," *Annual Review of Psychology*, vol. 52, no. 1, pp. 1-26, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[12] Mustafa Emirbayer, and Ann Mische, "What is Agency?," *American Journal of Sociology*, vol. 103, no. 4, pp. 962-1023, 1998. [CrossRef] [Google Scholar] [Publisher Link]

[13] Gemma Corbalan, Liesbeth Kester, and Jeroen J.G. Van Merriënboer, "Towards a Personalized Task Selection Model with Shared Instructional Control," *Instructional Science*, vol. 34, no. 5, pp. 399-422, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[14] Katharina Scheiter, and Peter Gerjets, "Learner Control in Hypermedia Environments," *Educational Psychology Review*, vol. 19, no. 3, pp. 285-307, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[15] Ben Williamson, *Big Data in Education: The Digital Future of Learning, Policy and Practice*, SAGE Publications, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Karen Yeung, "Hypernudge: Big Data as a Mode of Regulation by Design," *Information, Communication and Society*, vol. 20, no. 1, pp. 118-136, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[17] Min Lan, and Xiaofeng Zhou, "A Qualitative Systematic Review on AI Empowered Self-Regulated Learning in Higher Education," *npj Science of Learning*, vol. 10, no. 1, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Alie Molly Verghis et al., "Beyond Personalization: Autonomy and Agency in Intelligent Systems Education," *Frontiers in Education*, vol. 10, pp. 1-4, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Ghaida S. Alrawashdeh, and Nathan M. Castillo, "Student Agency in Personalized and Adaptive Learning Technologies: From Conceptualization to Application," *Education and Information Technologies*, vol. 30, no. 18, pp. 26125-26149, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] Bui Thi Dien et al., "Research on Proposing an Adaptive Educational Model for General Education in Vietnam," *Vietnam Journal of Educational Sciences*, vol. 2, no. 2, pp. 14-22, 2022. [Publisher Link]

[21] Gia Khuong An, and Thi Thuy An Ngo, "Unravelling Success in AI-Powered Personalized Learning in Vietnam: A Study on the Interplay of Platform Features and Psychological Responses," *Journal of Information Technology Education: Research*, vol. 24, pp. 1-48, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[22] Edward L. Deci, and Richard M. Ryan, "The "what" and "why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior," *Psychological Inquiry*, vol. 11, no. 4, pp. 227-268, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[23] Jory Brass, and Tom Liam Lynch, "Personalized Learning: A History of the Present," *Journal of Curriculum Theorizing*, vol. 35, no. 2, pp. 3-21, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[24] Neil Selwyn, "What's the Problem with Learning Analytics?," *Journal of Learning Analytics*, vol. 6, no. 3, pp. 11-19, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] Richard M. Ryan, and Edward L. Deci, "Intrinsic and Extrinsic Motivation from a Self-Determination Theory Perspective: Definitions, Theory, Practices, and Future Directions," *Contemporary Educational Psychology*, vol. 61, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[26] Ali Darvishi et al., "Impact of AI Assistance on Student Agency," *Computers and Education*, vol. 210, pp. 1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Vincen Aleven et al., "Help Seeking and Help Design in Interactive Learning Environments," *Review of Educational Research*, vol. 73, no. 3, pp. 277-320, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[28] Klarisa I. Vorobyeva et al., "Personalized Learning through AI: Pedagogical Approaches and Critical Insights," *Contemporary Educational Technology*, vol. 17, no. 2, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[29] E.L. Bjork, and R.A. Bjork, *Making Things Hard on Yourself, but in a Good Way: Creating Desirable Difficulties to Enhance Learning*, Psychology and the Real World: Essays Illustrating Fundamental Contributions to Society, pp. 56-64, 2011. [Google Scholar]

[30] Dragan Gašević, Shane Dawson, and George Siemens, "Let us not forget: Learning Analytics are about Learning," *TechTrends*, vol. 59, no. 1, pp. 64-71, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[31] B. Cardeñas Leezile et al., "Assessing the Pedagogical Limitations of Duolingo in English Language Instruction: Implications for Curriculum Development," *International Journal of Research in Education Humanities and Commerce*, vol. 6, no. 2, pp. 347-356, 2025. [CrossRef] [Publisher Link]

[32] Sari Mahibatus Saniyah, "Duolingo and Learner Autonomy: Investigating the Role of Personalization and Gamification in Promoting Self-Directed Language Learning," *ENJEL: English Journal of Education and Literature*, vol. 2, no. 2, pp. 141-147, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] Annisa Hafizah Gamal, Afrianto Daud, and Eliwarti, "Levelling up Writing: Investigating Duolingo's Gamification Effect on EFL Students' Writing Skills," *European Journal of English Language Studies*, vol. 5, no. 3, pp. 191-203, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[34] Yi Ma, and Mingyang Chen, "The Human Touch in AI: Optimizing Language Learning through Self-Determination Theory and Teacher Scaffolding," *Frontiers in Psychology*, vol. 16, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[35] Judy Kay, "Scrutable Adaptation: Because we can and must," *Adaptive Hypermedia and Adaptive Web-based Systems*, Lecture Notes in Computer Science, Springer, Berlin, Heidelberg, vol. 4018, pp. 11-19, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[36] Roger Azevedo, and Allyson F. Hadwin, "Scaffolding Self-Regulated Learning and Metacognition: Implications for the Design of Computer-based Scaffolds," *Instructional Science*, vol. 33, no. 5-6, pp. 367-379, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[37] Wayne Holmes, and Fengchun Miao, *Guidance for Generative AI in Education and Research*, Unesco Publishing, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[38] Simon J. Buckingham Shum, and Rosemary Luckin, "Learning Analytics and AI: Politics, Pedagogy and Practices," *British Journal of Educational Technology*, vol. 50, no. 6, pp. 2785-2793, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[39] Hassan Khosravi et al., "Explainable Artificial Intelligence in Education," *Computers and Education: Artificial Intelligence*, vol. 3, pp. 1-22, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[40] Davy Tsz Kit Ng et al., "Conceptualizing AI Literacy: An Exploratory Review," *Computers and Education: Artificial Intelligence*, vol. 2, pp. 1-11, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[41] Duri Long, and Brian Magerko, "What is AI Literacy? Competencies and Design Considerations," *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, Association for Computing Machinery, New York, United States, pp. 1-16, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[42] Zipei Ouyang, "Self-regulated Learning and Engagement as Serial Mediators between AI-Driven Adaptive Learning Platform Characteristics and Educational Quality: A Psychological Mechanism Analysis," *Frontiers in Psychology*, vol. 16, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[43] Ryan S. Baker, and Aaron Hawn, "Algorithmic Bias in Education," *International Journal of Artificial Intelligence in Education*, vol. 32, no. 4, pp. 1052-1092, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[44] Wayne Holmes et al., "Ethics of AI in Education: Towards a Community-Wide Framework," *International Journal of Artificial Intelligence in Education*, vol. 32, no. 3, pp. 504-526, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[45] Paul Prinsloo, and Sharon Slade, "An Elephant in the Learning Analytics Room: The Obligation to Act," *Proceedings of the Seventh International Learning Analytics and Knowledge*, Association for Computing Machinery, New York, United States, pp. 46-55, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[46] Sharon Slade, and Paul Prinsloo, "Learning Analytics: Ethical Issues and Dilemmas," *American Behavioral Scientist*, vol. 57, no. 10, pp. 1510-1529, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[47] Manos Antoninis et al., "*Global Education Monitoring Report 2023: Technology in Education — A Tool on whose Terms?*," UNESCO, Paris, France, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[48] How many Children and Young People have Internet Access at Home? Estimating Digital Connectivity during the COVID-19 Pandemic, UNICEF, 2020. [Google Scholar] [Publisher Link]