

Graphical abstract

## INTRODUCTION

AI-driven adaptive functions are now widely embedded in digital education platforms, yet their relationship to student engagement remains conceptually under-specified. Education 4.0 discourse emphasizes data-rich, responsive learning environments and has helped move personalization claims into mainstream platform design.<sup>[1]</sup> However, quality-focused digital education also requires that adaptation be assessed by its contribution to inclusive, meaningful participation in learning, rather than by novelty or automation alone, which aligns this agenda with SDG 4, Quality Education.<sup>[1, 2]</sup>

Despite rapid adoption, discussion of adaptive e-learning often reduces to a broad promise of

personalization, while engagement is treated as a narrow proxy for activity such as logins, clicks, or time on task. This definitional slippage is a practical failure mode for interpretation, because it limits comparability across systems, obscures what evidence actually supports, and makes defensible claims about how adaptation supports learners across varied instructional contexts difficult in the contemporary AI in education landscape.<sup>[3]</sup> The motivating problem landscape is summarized in Fig. (1). Building on these concerns, this study therefore argues for **engagementcentredframing** that separates what the system adapts, what learner state it infers, and which engagement dimension is intended to change.

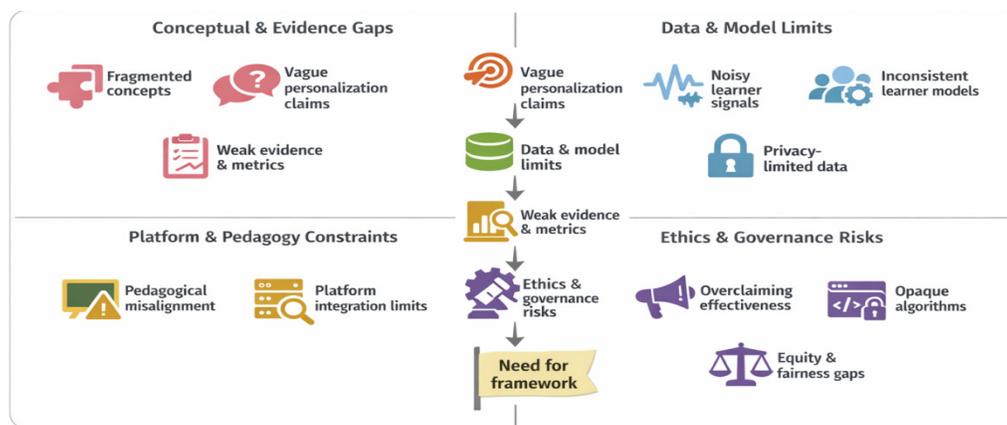


Fig. 1: Adaptive learning problem landscape

The paper contributes an organizing framework that links learner data signals, learner modeling, adaptive actions, engagement dimensions, and platform constraints into a single interpretive structure. Taken together, these categories are intended to help researchers and designers describe adaptive mechanisms precisely, locate where evidence supports a specific engagement claim, and differentiate plausible engagement support from overgeneralized effectiveness language. The remaining sections define the key constructs, build the framework, and show how it can be applied to recognizable adaptive platform patterns without substituting illustration for empirical proof.

### DOMAIN BACKGROUND AND PROBLEM FRAMING

Existing systematic syntheses of AI powered adaptive learning describe varied mechanisms and outcomes,

however they often treat engagement as activity rather than as a defined construct.<sup>[4]</sup> By contrast, work in artificial intelligence in education (AIED) blends learner modeling, recommendation, and tutoring paradigms, fragmenting claims through unshared assumptions.<sup>[5]</sup> Fig. (2) situates these clusters and gaps, clarifying the need for a disciplined organizing framework.

### Adaptive mechanisms and the data-to-action pipeline

Adaptive e-learning systems can be viewed as a data-to-action pipeline with three linked components: learner signals, a learner model that diagnoses learner state, and interventions that act on that diagnosis.<sup>[6]</sup> Learner signals include platform traces that are often informative, however they should not be treated as engagement by default and require interpretation before they are used as evidence. The pipeline components are summarized in Tab. (1).

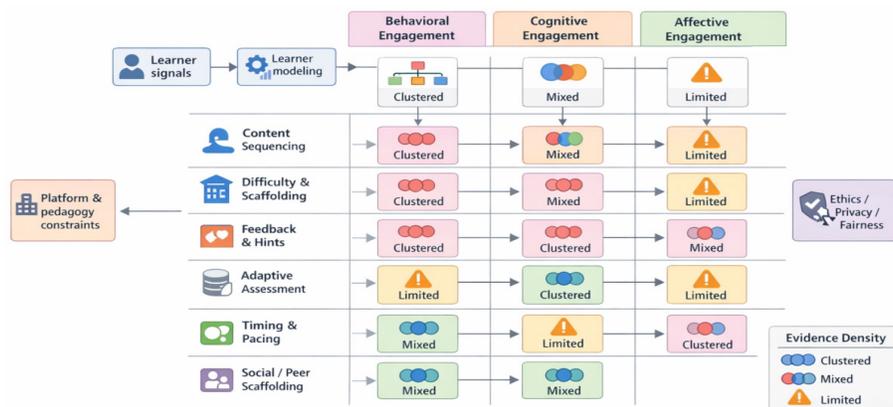


Fig. 2: Evidence map of adaptive learning literature

Table 1: Signals to model to action overview

| Pipeline Part          | What It Covers in This Paper   | Why It Matters for Engagement  |
|------------------------|--|--|
| Learner Signals        | Learner data signals from digital education platforms                            | Input evidence for engagement-centered adaptation (avoid treating simple activity metrics as engagement) |
| Learner Model          | Learner modeling that organizes learner data into an interpretable learner state | Connects signals to a defensible basis for personalization claims  |
| Adaptive Action        | Main categories of adaptive action used in adaptive learning and personalization | System responses intended to support student engagement in the learning journey                          |
| Context And Guardrails | Platform and pedagogical context plus ethics and governance constraints          | Sets boundaries, limits overclaim, and keeps adaptive design tied to real platform conditions            |

Learner modeling combines these inputs into an interpretable learner state, so personalization claims are anchored in model-based evidence rather than raw activity counts.<sup>[7]</sup> As updates accumulate, an adaptive action is selected so its engagement target matches inferred needs, while remaining consistent with platform constraints, pedagogy, and governance guardrails.<sup>[6, 7]</sup>

### Where engagement talk breaks down in platforms

Digital platforms often define engagement in terms of what is easiest to record: clicks, time on task, and submission counts. These traces are then treated as engagement itself, or as evidence of learning, even though they capture only a behavioral surface and can reflect compliance, confusion, or gaming.<sup>[8]</sup>

AI-mediated interaction can widen access to timely support through adaptive prompts or conversational help. However, it can also strain social boundaries by shifting expectations of responsiveness and by obscuring who is accountable for guidance.<sup>[8]</sup> Because platforms must work within privacy constraints, limited context about learners, and classroom pedagogy, adaptation is most credible when it targets specific engagement dimensions and avoids optimizing simplistic proxies that can be improved without improving learning.

### KEY CONCEPTS AND DEFINITIONAL BOUNDARIES

Key terms are set to keep the scope on engagement-centred adaptive learning in digital platforms, rather than on benchmarking. Adaptive learning is defined as system change driven by learner data and models. Personalization is defined as learner-specific adjustment. Engagement is treated as comprising behavioral, cognitive, and affective components, and it is differentiated from activity counts, learning outcomes, and policy-framed expectations for digital literacy or competence.<sup>[9, 10]</sup> Definitions are provided in Tab. (2), and their relations are summarized in Fig. (3). Engagement components are stated in Eq. (1).

$$e = (E_b, E_c, E_a) \tag{1}$$

A composite index is stated in Eq. (2).

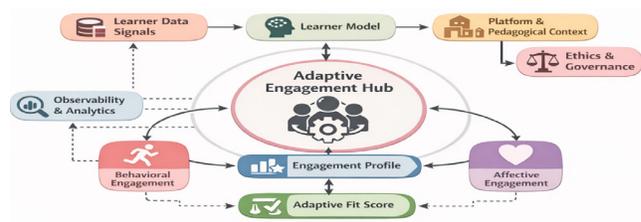


Fig. 3: Conceptual framework for key terms

Table 2 : Definitions and scope boundaries

| Term                                  | Meaning In This Paper   | Scope Boundary  |
|---------------------------------------|---|---|
| AI-driven adaptive e-learning systems | Digital learning systems that use AI to adjust learning experiences and support student engagement                  | Focus is on engagement-centered adaptation in digital platforms, not algorithm benchmarking |
| Adaptive learning                     | System changes based on learner data and a learner model to choose an adaptive response                             | Kept to adaptation logic and design choices, not claims of universal effectiveness          |
| Personalization                       | Learner-specific adjustments made through adaptive functions rather than one-size-fits-all delivery                 | Treated as a design approach; avoids generic personalization claims and overclaim           |
| Student engagement                    | A construct treated as more than simple activity; discussed through behavioral, cognitive, and affective components | Separated from learning outcomes; activity metrics alone are not treated as engagement      |
| Digital education platform context    | The platform and pedagogical conditions that shape what adaptation can do and how engagement is expressed           | Used to keep interpretations realistic; excludes broad AI policy discussion                 |

### Student engagement as a multi-component construct

Student engagement is treated as a **multi-component state** that integrates behavioral participation, cognitive investment, and affective experience during learning activities. Engagement is therefore not presented as a fixed trait but as a changing state shaped by attention, challenge, and perceived control, aligning with flow-oriented accounts of absorption and persistence in tasks.<sup>[11]</sup>

Engagement is also situated in social and institutional contexts in which meaning is produced through community norms and patterns of participation.<sup>[12]</sup> This distinction clarifies how adaptive interventions should be interpreted: personalization that optimizes an individual’s momentary motivation may not strengthen belonging, collaboration, or legitimate participation, while, by contrast, socially supportive design can sustain engagement even when task-level flow fluctuates.<sup>[11, 12]</sup>

### Adaptation vs personalization and the boundary of claim

Adaptive behaviour denotes system decisions that adjust in response to an inferred learner state and context, most often via learner modeling. This usage clarifies a narrower category within the broader label personalization, which may include adaptive behaviour but also static tailoring. By contrast, customization refers to simpler options set by a user or instructor and does not rely on ongoing inference.<sup>[13]</sup>

In the evaluated framing, claims are restricted to changes in engagement, including attention, participation, or persistence within a platform. However, effectiveness claims about learning outcomes require separate theory and evidence and should not be implied by the term personalization alone, given the risk of conflating engagement with learning.<sup>[13]</sup>

### Learner modeling and digital platform context

Learner modeling in this setting is an interpretable, updatable estimate of learner state inferred from platform traces and learner inputs. Logs provide the observed evidence (e.g., progress, errors, timing).

By contrast, the model represents the inferred state that is then used to select adaptive actions.

Platform context covers content formats, interaction tools, and observable signals, while pedagogical context covers sequencing, assessment stakes, pacing, and instructor or peer support. These conditions constrain what adaptation can do and clarify how engagement indicators should be interpreted, so simple activity counts are not treated as engagement.

### FRAMEWORK CONSTRUCTION

The framework organizes adaptive e-learning around engagement by linking learner state, candidate actions, and intended engagement targets, building on efficiency-oriented summaries.<sup>[14]</sup> Fig. (4) clarifies these links for design and interpretation. Engagement gain is the predicted change after action a, Eq. (3).

$$\Delta E(s, a, t) = \hat{E}(s', t) - \hat{E}(s, t) \tag{3}$$

Adaptive fit differentiates actions by weighing gain against implementation cost and governance risk, Eq. (4).

$$Fit(s, a, t) = \Delta E(s, a, t) - \lambda Cost(a) - \mu Risk(a) \tag{4}$$

Action selection chooses the option with maximum fit among those available, Eq. (5).

$$a^* = \max_{a \in A} Fit(s, a, t) \tag{5}$$

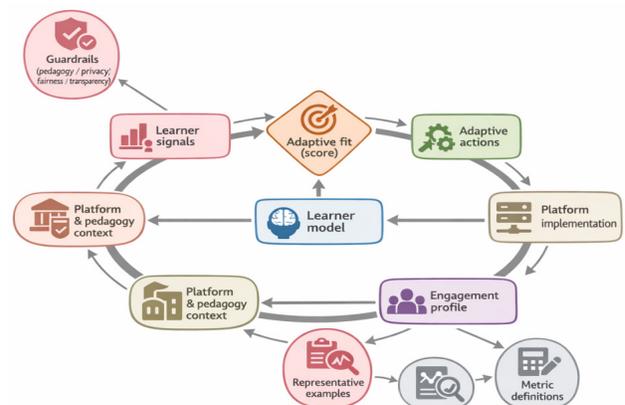


Fig. 4: Logic model linking data, actions, and engagement

### Core elements of the engagement-centred adaptive framework

The engagement-centred adaptive framework clarifies how an adaptive digital learning platform can translate learner information into actions intended to support engagement. It organizes this process into learner data signals, a learner model that interprets those signals, adaptive actions that modify the learning experience, engagement dimensions that specify the intended target of change, and contextual constraints that bound what adaptation can reasonably claim or do.

Learner data signals are the observable traces available to the platform, including interaction, timing, and assessment events, which become informative only after appropriate cleaning and interpretation. The **learnermodel** represents the learner state inferred from these signals and provides the basis for selecting adaptive actions such as content selection, pacing support, feedback, or interface changes. Engagement dimensions specify what the action aims to influence, differentiating participation behaviours from cognitive investment and affective experience. The mechanism map in Fig. (5) situates signals, model, action, and engagement target within a single decision pathway.

Finally, **contextualconstraints** differentiate the settings in which adaptation is feasible by capturing

pedagogy, course design, privacy, and fairness limits. The blueprint also underscores that the goal is to balance engagement rather than to maximize activity.”

### Linking learner state, adaptive action, and engagement targets

Adaptive e-learning systems typically depend on an inferred learner state to decide what should be changed in the platform. Learner data signals, such as participation traces, are interpreted through learner modeling to summarize behavioral, cognitive, and affective engagement conditions, while also accounting for constraints imposed by the platform and pedagogy. These inferred states, in turn, delimit what an adaptive response can plausibly influence.

The framework therefore represents each adaptation as a matched triple consisting of the current state, a specific adaptive action, and an explicit engagement target. The **state action target alignment** clarifies that personalization decisions should be chosen to address participation patterns (behavioral), learning needs (cognitive), or engagement support needs (affective), while context-state adaptations remain constrained (Tab. (3)).

By explicitly naming the target dimension, the framework supports more disciplined, scope-limited claims about how platform features

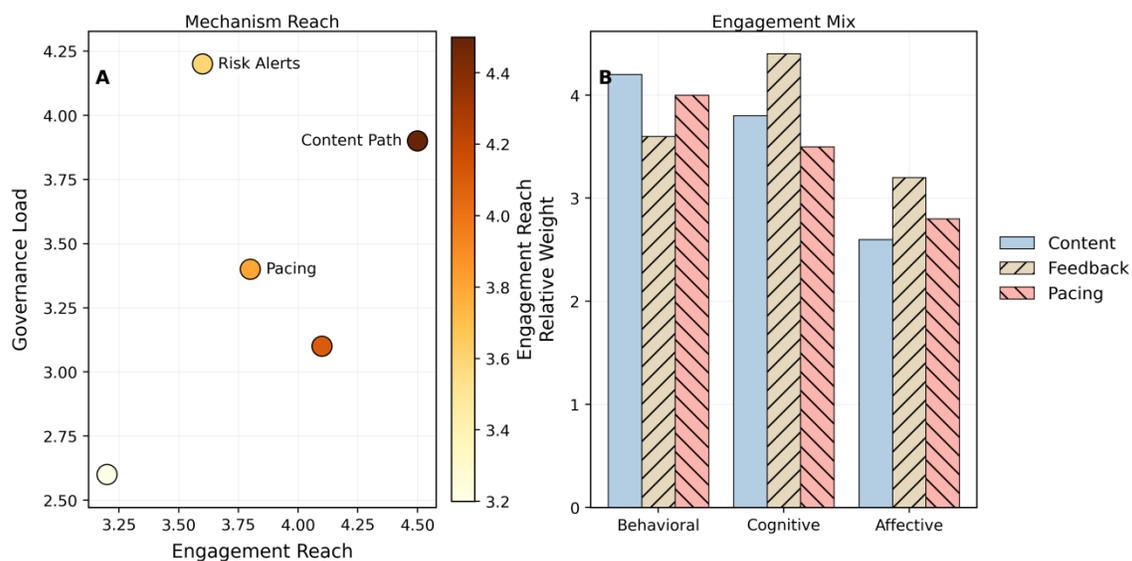


Fig. 5: Adaptive engagement blueprint

**Table 3: State action target alignment**

| Learner State                          | Learner Data Basis  | Adaptive Action   | Engagement Target                                  |
|--|---|---|--|
| Behavioral engagement state            | Learner data signals in digital platforms, interpreted through learner modeling | Adaptive learning personalization choice matched to current participation patterns        | Behavioral engagement                              |
| Cognitive engagement state             | Learner data signals, interpreted through learner modeling                      | Adaptive learning personalization choice matched to current learning needs                | Cognitive engagement                               |
| Affective engagement state             | Learner data signals, interpreted through learner modeling                      | Adaptive learning personalization choice matched to engagement support needs              | Affective engagement                               |
| Platform and pedagogical context state | Digital platform context and pedagogical context constraints                    | Adaptive learning personalization constrained by platform realities and governance limits | Student engagement (within contextual constraints) |

may shape engagement through self-regulated learning processes, rather than assuming that any personalization increases engagement.<sup>[15]</sup> This framing also aligns with mediation-based reasoning in which adaptive actions operate through intermediate learner processes before changes in engagement are observed.<sup>[15]</sup>

### How the framework is used to read systems and studies

The framework serves as a reading template for adaptive e-learning systems or studies by requiring a full chain from learner data signals to a learner model, from the model to an adaptive action, and from that action to the specific engagement dimension it is meant to affect. Contextual conditions, including course design, platform affordances, and governance limits, are documented alongside the chain so that interpretation remains situated

Applying the same template across studies clarifies comparisons and makes overclaim harder to sustain. Claims are expected to track the stated targets, mechanisms, and constraints, rather than defaulting to generic personalization.

### APPLYING THE FRAMEWORK TO ADAPTIVE PLATFORM PATTERNS

On digital platforms, the framework can be interpreted as a set of recurring design patterns: learner signals

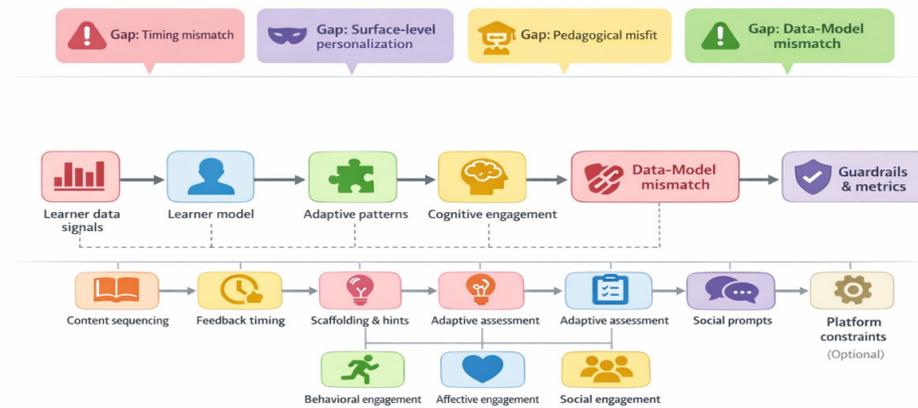
are first condensed into a learner model and then translated into an adaptive action that targets a particular engagement dimension within platform constraints. Common instances include adjusting content sequence or difficulty, scheduling feedback or reminders, recommending practice based on identified gaps, and offering choice or social prompts that are intended to sustain motivation while avoiding claims of universal learning gains.

### Common adaptation patterns and their engagement focus

Adaptive e-learning systems often implement recurring adaptation patterns, yet the engagement purpose of an adaptive action is frequently left implicit. For claim discipline, **engagement-target specificity** requires describing the action by the engagement dimension it aims to shift, not only by proxies such as clicks or time-on-task.<sup>[16]</sup>

The crosswalk in Tab. (4) treats engagement as a profile with behavioral, cognitive, and affective components and links each component to the way the platform frames adaptation. Behavioral targets emphasize observable participation, cognitive targets emphasize effortful processing and understanding, and affective targets emphasize interest and emotional tone during learning.

Retrieval practice, including practice testing, is a canonical adaptive pattern because item selection



**Fig. 6: Mismatch map of adaptation patterns and engagement**

**Table 4: Patterns mapped to engagement dimensions**

| Engagement Type | How Engagement Is Framed                       | How Adaptation Connects  |
|-----------------|--|--|
| Behavioral      | Behavioral component of the engagement profile | Used as an intended engagement target when matching learner state, adaptive response, and platform context                                     |
| Cognitive       | Cognitive component of the engagement profile  | Used as an intended engagement target when linking learner data signals and learner modeling to adaptive actions                               |
| Affective       | Affective component of the engagement profile  | Used as an intended engagement target when interpreting how adaptive actions support student engagement without generic personalization claims |

and spacing can be tuned to a learner model and an intended cognitive engagement target.<sup>[17]</sup> However, mismatches arise when the same technique is justified only by behavioral activity gains, or applied without regard to task and context constraints.<sup>[16]</sup> The mismatch map in Fig. (6) summarizes these common target-technique gaps.

### Illustrative literature-backed examples and interpretations

An explainable AI (XAI) engagement modeling example can be read as connecting platform logs to a learner model, with explanations used to justify an adaptive response, for example adjusting feedback to sustain behavioral participation rather than inferring motivation.<sup>[18]</sup> On this reading, key limitations are explicit from the outset, including imperfect proxy signals and the risk that explanations do not correspond to causal mechanisms.

Large scale analytics can reveal patterns across learners, however the framework depends on spec-

ifying both what is adapted and which engagement dimension is targeted, instead of treating prediction accuracy as evidence of personalization [18]. Small sample learning management system (LMS) studies can make these categories concrete by documenting the adapted element, such as content sequencing or support messages, and the claimed engagement form, but conclusions remain bounded by the local platform and pedagogy.<sup>[19]</sup>

### DISCUSSION AND IMPLICATIONS

The framework clarifies personalization by differentiating which learner signals warrant which adaptive actions and which engagement dimensions the adaptation targets. Interpretation and design are treated as context-sensitive decisions, shaped by pedagogy, platform constraints, and governance limits, not as universal improvement claims. Responsible use in the evaluated setting requires identifying where evidence is missing and avoiding one-size-fits-all narratives when translating design guidance.<sup>[20]</sup>

### Implications for research design and platform practice

Evaluations of adaptive engagement should start from explicit definitions and measures that distinguish engagement from activity counts and from learning outcomes, so that claims remain aligned with what is observed. Carefully designed comparisons can then examine whether adaptive actions, driven by learner signals and learner models, shift targeted engagement dimensions, while also recording practical constraints on follow up, baseline collection, and implementation.<sup>[21]</sup>

In platform settings, instrumentation should capture the signals required by the intended adaptation, and reporting should situate the evidence by stating the platform context and scope and by clarifying that it reflects conceptual synthesis rather than new experiments. A compact set of reporting checks is summarized in Tab. (5).

### Guardrails: privacy, fairness, transparency, and feasibility

Adaptive engagement systems are shaped by governance and platform constraints that limit which

**Table 5: Operationalization and reporting guidance**

| Reporting Check                      | What To State   | Why It Matters  |
|--------------------------------------|---|---|
| Define Key Terms                     | Clear meanings for adaptation, personalization, engagement, learner modeling, and digital platform context  | Prevents concept drift across the paper and avoids undefined buzzwords                |
| Separate Engagement from Outcomes    | How student engagement is treated differently from simple activity metrics and from learning outcomes   | Avoids overstating what engagement signals mean and keeps interpretation disciplined  |
| Describe Adaptive Logic              | How learner data signals and learner models connect to adaptive actions and intended engagement dimensions  | Prevents generic personalization claims and makes the framework usable                |
| State Platform Context and Scope     | Digital education platform setting, intended use context, and what the paper keeps in and keeps out   | Keeps the framework tied to real platform conditions and controls overgeneralization  |
| Keep Claims Aligned to Evidence Type | That the manuscript is a conceptual framework paper, uses literature synthesis and illustrative examples, and does not present original empirical results | Reduces overclaim risk and helps readers judge the strength and limits of conclusions |

**Table 6: Risks and recommended checks**

| Risk                         | Why It Matters   | Recommended Check  |
|------------------------------|--|--|
| Concept Drift                | Framework becomes vague if key terms are used inconsistently                           | Lock definitions for adaptation, personalization, student engagement, learner modeling, digital platform context; use terms consistently across sections |
| Engagement Over-Simplified   | Activity metrics can be mistaken for engagement, weakening interpretation              | Separate engagement from simple activity metrics; describe engagement dimensions explicitly when discussing adaptive actions                             |
| Overclaiming Personalization | Generic personalization talk can imply universal effectiveness, beyond the paper scope | Avoid claims about universal effectiveness; keep claims tied to what the conceptual framework clarifies and how it should be used                        |

| Risk                          | Why It Matters  | Recommended Check  |
|-------------------------------|---|--|
| Examples Treated as Evidence  | Illustrations can read like original empirical findings                                 | Label examples as literature-backed illustrations; represent published sources accurately; avoid case-study framing that implies new results |
| Ignoring Platform Constraints | Adaptive design can be described without real platform limits, reducing practical value | Include implementation and ethics constraints that shape adaptive design: privacy, fairness, transparency, platform and pedagogical context  |

learner data may be used and which adaptive actions are defensible. Privacy requires data minimization, informed consent, and limits on secondary use. Transparency requires that learners and instructors can understand why adaptations occur. Feasibility requires alignment with course pedagogy and platform capabilities.<sup>[22]</sup>

Implementation and overclaim risks, and recommended checks for maintaining disciplined interpretation, are summarized in Tab. (6). Fairness should be evaluated for potential disparate impact across subgroups by comparing each subgroup engagement estimate with a reference value, Eq. (6).

$$Gap_g = |E_g - E_{ref}| \quad (6)$$

## CONCLUSION

This study develops an engagement-centred framework to interpret AI-driven adaptive e-learning on digital education platforms, clarifying how learner signals inform learner modeling, how models drive adaptive actions, and which engagement dimension each intervention aims to shift. By differentiating engagement from simple activity traces and from learning outcomes, the framework supports defensible, comparable research claims and makes the main points of missing evidence explicit. For platform design, it provides a practical template to align instrumentation, adaptation choices, and governance guardrails, including privacy, fairness, and transparency. Taken together, the framework situates conceptual precision as a prerequisite for responsible personalization.

## REFERENCES

1. A. A. Hussin, "Education 4.0 made simple: Ideas for teaching," *International journal of education and literacy studies*, vol. 6, no. 3, pp. 92-92, July 2018, doi: 10.7575/aiac.ijels.v.6n.3p.92.
2. S. Singh, E. Sengupta, M. Saini, and M. Singh, "Role of artificial intelligence technology in learning environments for achieving the sustainable development goal of quality education (SDG 4) by 2030," *International Journal on Advanced Computer Theory and Engineering*, vol. 15, no. 1S, pp. 1-10, 2026, Available: <https://journals.mriindia.com/index.php/ijacte/article/view/1297>
3. M. A. Chaudhry and E. Kazim, "Artificial intelligence in education (AIEd): A high-level academic and industry note 2021," *AI and Ethics*, vol. 2, no. 1, pp. 157-165, July 2021, doi: 10.1007/s43681-021-00074-z.
4. H. Hariyanto, F. X. D. Kristianingsih, and R. Maharani, "Artificial intelligence in adaptive education: A systematic review of techniques for personalized learning," *Discover Education*, vol. 4, no. 1, Oct. 2025, doi: 10.1007/s44217-025-00908-6.
5. F. Ouyang and P. Jiao, "Artificial intelligence in education: The three paradigms," *Computers and Education Artificial Intelligence*, vol. 2, pp. 100020-100020, Jan. 2021, doi: 10.1016/j.caeai.2021.100020.
6. D'Costa, M. (2025). Artificial Intelligence-Driven Adaptive E-Learning Systems for Personalized Student Engagement: A Comprehensive Review. *International Journal on Research and Development - A Management Review*, 14(1), 397-405.
7. F. Böck, M. Ochs, A. Henrich, D. Landes, J. L. Leidner, and Y. Sedelmaier, "Learner models:

- Design, components, structure, and modelling,” *User Modeling and User-Adapted Interaction*, vol. 35, no. 4, Nov. 2025, doi: 10.1007/s11257-025-09434-4.
8. K. Seo, J. Tang, I. Roll, S. Fels, and D. Yoon, “The impact of artificial intelligence on learner-instructor interaction in online learning,” *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, pp. 54-54, Oct. 2021, doi: 10.1186/s41239-021-00292-9.
  9. R. J. Krumsvik, “Teacher educators’ digital competence,” *Scandinavian Journal of Educational Research*, vol. 58, no. 3, pp. 269-280, Oct. 2012, doi: 10.1080/00313831.2012.726273.
  10. J. Voogt, O. Erstad, C. Dede, and P. Mishra, “Challenges to learning and schooling in the digital networked world of the 21st century,” *Journal of Computer Assisted Learning*, vol. 29, no. 5, pp. 403-413, Sept. 2013, doi: 10.1111/jcal.12029.
  11. D. J. Shernoff, M. Csíkszentmihályi, B. Shneider, and E. S. Shernoff, “Student engagement in high school classrooms from the perspective of flow theory.” *School Psychology Quarterly*, vol. 18, no. 2, pp. 158-176, Jan. 2003, doi: 10.1521/scpq.18.2.158.21860.
  12. M. Bloch, J. Lave, and É. Wenger, “Situated learning: Legitimate peripheral participation.” *Man*, vol. 29, no. 2, pp. 487-487, June 1994, doi: 10.2307/2804509.
  13. Asadullah, D. Sinha, S. Kumar, R. Kumari, A. Kaur, and J. Kaur, “Artificial intelligence in personalised learning system,” *International Journal on Research and Development - A Management Review*, vol. 15, no. 1, pp. 112-120, 2026, Available: <https://journals.mriindia.com/index.php/ijrd-mr/article/view/1727>
  14. M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, “AI-based personalized e-learning systems: Issues, challenges, and solutions,” *IEEE Access*, vol. 10, pp. 81323-81342, Jan. 2022, doi: 10.1109/access.2022.3193938.
  15. Z. 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. 1646469-1646469, Oct. 2025, doi: 10.3389/fpsyg.2025.1646469.
  16. Nagamani, N. (2023). A comparative analysis of classical and quantum machine learning models for financial fraud detection. *Computer Fraud & Security*, 2023(12), 58-63. <https://doi.org/10.52710/cfs.895>
  17. Smith, O. J. M. (2025). FPGA-Accelerated GNN Pipelines for Real-Time Identity Threat Scoring in Zero-Trust Cloud Systems. *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, 2(3), 17-25.
  18. B. Bali, “Cognitively-informed explainable AI for education: Enhancing student engagement and transparent assessment through human-centered modeling,” *Journal of Social and Scientific Education*, vol. 2, no. 3, pp. 173-190, Sept. 2025, doi: 10.58230/josse.v2i3.351.
  19. Rafizadeh, H. (2025). Adaptive Learning in the Era of Artificial Intelligence: Enhancing Student Engagement in Digital Education. *International Journal on Advanced Computer Engineering and Communication Technology*, 14(1), 786-795.
  20. Jadhav, K. D., Narayana, A., Chaudhari, L. B., Monisha J., Ambhore, V., & Shelke, G. C. (2026). AI-GENERATED LEARNING RESOURCES FOR CREATIVE FIELDS. *ShodhKosh: Journal of Visual and Performing Arts*, 7(1s), 147-157. <https://doi.org/10.29121/shodhkosh.v7.i1s.2025.7080>.
  21. Attapong, S. (2025). AI-Enabled Personalization in Digital Learning Platforms: A Review of Adaptive E-Learning Technologies. *International Journal of Recent Advances in Engineering and Technology*, 14(1), 226-234.
  22. Barhani, D., & Kharabi, P. (2025). Peer-Assisted Learning Systems over Intelligent Wireless Networks. *Journal of Wireless Intelligence and Spectrum Engineering*, 1-6.
  23. Sule, B., & Oruganti, S. K. (2026). EdTech-Microfinance Integration: Designing Intelligent Learning Systems to Enhance Credit Discipline and Enterprise Growth. *Enterprise Development and Microfinance*, 35(2), 368-389. <https://doi.org/10.3362/edm.v35i2.579>