A Conceptual Framework for the Relationship between Learning Analytics Dashboard, Adaptive Environments, and Self-Regulated Learning

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Abstract:

The digital transformation of higher education has created an urgent demand for intelligent systems that move beyond digital content delivery toward adaptive, data-driven ecosystems. This paper introduces a conceptual framework integrating three foundational pillars: Learning Analytics Dashboard (LAD), Adaptive Environments (AE), and Self-Regulated Learning (SRL). While earlier studies examined these elements individually or in pairs, their comprehensive integration remains limited. Through a conceptual–analytical review of 55 international and regional studies (2019–2024), the paper proposes the Self-Generating Adaptive Learning Loop: a cyclical model where LAD capture and visualize real-time learner data, AE translate analytics into adaptive pathways, and SRL provides the pedagogical anchor for goal-setting, monitoring, and reflection. The study contributes theoretically by extending dual models into a unified framework and practically by offering implementation guidelines for LMS design—emphasizing LAD integration, adaptive sequencing, and SRL scaffolds. Pedagogical implications include enhanced autonomy, persistence, and reduced dropout, while technological implications highlight the importance of interoperable data pipelines and enriched learner models. Despite its conceptual focus, the study outlines a clear agenda for empirical validation, longitudinal outcome assessments, and design-based refinements of adaptive dashboards. Overall, the framework advances both scholarship and practice by providing a credible pathway toward learner-centered ecosystems that are personalized, reflective, and data-driven.

Keywords:

Learning Analytics Dashboard (LAD); Adaptive Environments (AE); Self-Regulated Learning (SRL); Educational Technology; Conceptual Framework; Data-Driven Learning; Personalized Learning; Adaptive Systems; Higher Education.

1- Introduction:

The digital transformation of higher education has fundamentally reshaped global teaching and learning practices. Today, more than 80% of universities employ LMS, and the global learning analytics market is projected to exceed USD 9 billion by 2027 (UNESCO, 2023; Statista, 2023). In the Middle East, e-learning adoption is expanding at an annual rate of 14–16%, largely driven by the demand for adaptive and personalized solutions (World Bank, 2023). These trends underscore an urgent need to move beyond basic digitalization toward intelligent systems capable of analyzing learner data, adapting instruction, and fostering self-regulated learning (SRL).

Within this transformation, three interrelated pillars have gained prominence. Learning Analytics Dashboard (LAD) provide real-time visualizations of learner behavior, transforming raw interaction data into interpretable insights (Verbert et al., 2013; Schwendimann et al., 2017). Adaptive Environments (AE) personalize learning pathways by tailoring content, feedback, and sequencing to learners' evolving needs (Graf & Kinshuk, 2007; Tseng et al., 2020). Self-Regulated Learning (SRL), conceptualized by Zimmerman (2002) and Pintrich (2000), refers to the learner's capacity to set goals, monitor progress, regulate motivation, and adapt strategies. Collectively, these dimensions signal a paradigm shift from teacher-centered instruction toward data-driven, learner-centered ecosystems.

Despite their individual significance, the integration of LAD, AE, and SRL remains underdeveloped. Existing studies have primarily explored LAD–SRL linkages, emphasizing dashboards' role in enhancing metacognition (Roll & Winne, 2015), or AE–analytics combinations aimed at adaptive sequencing (Azevedo & Gašević, 2019). Yet few attempts have produced a comprehensive tripartite model in which LAD feed adaptive engines, AE scaffold SRL processes, and SRL behaviors, in turn, generate new data for dashboards (Matcha et al., 2019; Zheng et al., 2021). Zimmerman's (2002) cyclical model—forethought, performance, and reflection—demonstrates the potential of a closed-loop design. LAD can visualize goals, issue predictive alerts, and support reflection, but without integration into adaptive environments, they risk remaining static and descriptive tools (Schwendimann et al., 2017).

Empirical evidence further illustrates both the potential and the limitations of current practice. Al-Shaer (2023) demonstrated that AE supported by LAD integration significantly enhanced university students' SRL skills, particularly in goal-setting and monitoring. Martha et al. (2023) reported similar improvements when LAD were embedded into LMS platforms. Elmabaredy and Gencel (2024) confirmed SRL gains from personalized dashboards, though their work did not incorporate adaptive mechanisms. In applied contexts, Vykopal et al. (2022) designed an intelligent cybersecurity training environment that integrated LAD to tailor tasks, yet self-regulation was not explicitly assessed. Collectively, these studies reveal partial integrations, but no comprehensive tripartite framework.

The urgency of integration is underscored by persistently high attrition rates: the OECD (2022) notes that dropout in online courses often exceeds 40%, driven largely by insufficient self-regulation and lack of adaptive support. LAD alone cannot reduce attrition without adaptive responses; AE alone cannot succeed without learners' regulatory capacity; and SRL itself requires analytics-driven scaffolds to be sustained.

This study responds to the identified gap by proposing a conceptual framework built on three interdependent components:

- LAD as real-time analytical mirrors that capture and visualize learner data.
- AE as adaptive engines that translate analytics into tailored scaffolds and instructional pathways.
- SRL as the pedagogical anchor that drives goal-setting, monitoring, and reflection.

The resulting cycle—Data → Analytics → Adaptation → Self-Regulation → New Data—transforms dashboards from descriptive tools into dynamic engines that foster autonomy and adaptive decision-making.

Beyond theory, the framework has clear practical applications. For educators, it enables course designs where analytics directly inform teaching practices. For developers, it highlights the necessity of linking visualization tools with adaptive engines. For learners, it ensures that feedback is timely, actionable, and personally meaningful, thereby enhancing persistence and motivation.

Policy directions reinforce this shift. For example, the European Commission (2022) emphasizes personalized learning supported by artificial intelligence, while universities worldwide are increasingly investing in adaptive LMS modules.

The role of SRL is pivotal: studies confirm its predictive power for achievement, persistence, and lifelong learning capacity (Panadero, 2017; Nicol & Macfarlane-Dick, 2006). Yet SRL does not emerge automatically—it requires intentional scaffolding. By embedding LAD-informed supports into AE, institutions can operationalize SRL in measurable ways. For instance, in a STEM course, a traditional dashboard may simply flag low participation, whereas in an integrated environment, the LAD not only signals the issue but also activates adaptive mechanisms that provide extra tasks, strategic prompts, and reflective guidance. The learner, in turn, adjusts behaviors and completes the cycle.

In sum, the convergence of analytics adoption, persistent attrition, and the demand for learner autonomy justifies the need for a tripartite model. The proposed framework addresses both theoretical and applied gaps by uniting LAD, AE, and SRL into a cohesive feedback loop, thereby advancing research and practice in educational technology.

2- Research Problem

Despite growing attention to LAD, AE, and SRL, the literature shows significant fragmentation. Most studies:

- Examine LAD without adaptive mechanisms.
- Focus on SRL without analytics.
- Design AE without explicit SRL scaffolds.

This lack of integration limits the potential of smart learning systems to deliver personalized, reflective, and data-driven experiences.

3- Research Question

How can an integrated conceptual framework combining LAD, AE, and SRL be constructed to enhance learner autonomy and adaptive decision-making in smart educational systems?

4- Research Objectives

This study aims to:

- Develop a conceptual framework aligning LAD and AE functions with SRL processes.
- Bridge theoretical and applied gaps by synthesizing educational, technological, and cognitive dimensions.
- Provide a design foundation for intelligent environments that foster SRL.
- Propose actionable recommendations for LMS implementation.

5- Significance of the Study

Theoretical Significance

Although LAD, AE, and SRL have been studied independently, they are rarely conceptualized together. By presenting a new theoretical model that unifies analysis, adaptation, and regulation into a continuous cycle, it also enhances understanding of how perception, adaptation, and teaching methods interact, providing a basis for empirical testing and future theory building.

Practical Significance, for practitioners, the framework provides actionable guidance:

- Empowering learners to monitor and regulate their learning.
- Enabling instructors to identify at-risk students in real time.
- Reducing dropout in online and blended contexts.
- Enhancing personalization and learner satisfaction.
- Supporting institutional and national strategies emphasizing AI-driven education.

Thus, the contribution extends beyond theory to offer a practical roadmap for transforming LMS into intelligent ecosystems that promote sustainable SRL.

6- Literature Review:

A. Learning Analytics Dashboard- (LAD):

LAD are among the most influential applications of learning analytics in higher education, providing visual interfaces that transform complex learner data into interpretable indicators for students and instructors (Verbert et al., 2013). Unlike static reports, modern LAD function as cognitive instruments, supporting reflection, monitoring, and evidence-based decision-making (Schwendimann et al., 2017).

Evolution: Early dashboards mainly reported LMS log data (Elias, 2011). Recent advances introduced predictive and AI-based dashboards capable of identifying at-risk learners and recommending personalized strategies (Schumacher & Ifenthaler, 2018; Matcha et al., 2019).

Pedagogical contributions: LAD foster metacognition and SRL by providing transparent indicators that enable goal-setting, monitoring, and reflection (Roll & Winne, 2015; Jivet et al., 2018). In Arab contexts, integration with adaptive mechanisms improved SRL skills such as goal-setting and monitoring (Al-Shaer, 2023; Martha et al., 2023).

Strengths: LAD offer real-time monitoring, personalization potential, dual utility for learners and teachers, and motivational benefits (Jivet et al., 2018).

Challenges: Many remain descriptive, focusing on superficial indicators or complex visualizations that overwhelm learners (Zheng et al., 2021). Concerns include overemphasis on instructor use and ethical issues of privacy and data ownership (Schumacher & Ifenthaler, 2018).

Integration: Dashboards support SRL phases by embedding forethought cues, performance indicators, and reflection prompts (Roll & Winne, 2015; Elmabaredy & Gencel, 2024). When linked with adaptive engines, LAD enrich personalization; without them, adaptive systems risk oversimplifying learner profiles (Vykopal et al., 2022).

Trends and gaps: Research emphasizes predictive LAD, SRL-focused designs, and adaptive dashboards. However, tripartite integration of LAD, AE, and SRL remains largely absent, especially in Arab higher education (Al-Shaer, 2023).

B. Adaptive Environments (AE)

AE evolved from intelligent tutoring systems and adaptive hypermedia (Brusilovsky, 2001). They leverage AI and analytics to personalize content, feedback, and pacing in response to learners' performance and preferences (Graf & Kinshuk, 2007; Tseng et al., 2020). Unlike static models, AE dynamically adjust instructional pathways to sustain engagement and prevent overload.

Pedagogical contributions: AE provide tailored instruction through content sequencing, real-time feedback, adaptive scaffolding, and learner grouping (Azevedo & Gašević, 2019). Empirical studies confirm their effectiveness across STEM, professional training, and higher education contexts (Tseng et al., 2020; Vykopal et al., 2022). In Arab contexts, AE supported by analytics enhanced SRL skills such as autonomy and time management (Al-Shaer, 2023).

Strengths: AE offer personalization at scale, promote learner empowerment, enhance engagement, and generate actionable data insights for instructors.

Challenges: Many rely on limited learner models (e.g., scores, clickstream data), producing surface-level adaptation (Graf & Kinshuk, 2007). Overemphasis on technology risks neglecting pedagogy, while issues of privacy, bias, and transparency persist (Schumacher & Ifenthaler, 2018). Institutional adoption is often constrained by cost and faculty resistance (Younis, 2024).

Integration with SRL: AE can embed scaffolds for goal-setting, reflection, and adaptive feedback (Roll & Winne, 2015). Studies show adaptive instructor feedback influences learners' regulation and emotional control (Zheng et al., 2021). Regional research demonstrates that AE informed by LAD data enhance both personalization and SRL (Al-Shaer, 2023).

Trends and gaps: Current directions include AI-enhanced adaptation, multimodal data (e.g., emotion recognition), and LMS integration. Still, tripartite models uniting AE, LAD, and SRL are rare, particularly in Arab higher education (Younis, 2024).

C. Self-Regulated Learning (SRL)

SRL is defined as learners' proactive ability to set goals, monitor progress, regulate strategies, and reflect on outcomes (Zimmerman, 2002; Pintrich, 2000). Zimmerman's cyclical model highlights forethought, performance, and reflection phases, while Pintrich emphasizes the interplay of motivation and cognition. SRL underscores learner agency and responsibility in digital and adaptive contexts.

Empirical contributions: SRL strongly predicts achievement, persistence, and lifelong learning (Panadero, 2017; Nicol & Macfarlane-Dick, 2006). In online and blended contexts, its importance grows due to reduced instructor presence. Studies show dashboards foster SRL by embedding reflective prompts (Jivet et al., 2018; Roll & Winne, 2015). Adaptive environments similarly promote SRL by providing tailored scaffolds and feedback (Zheng et al., 2021). Arab studies confirmed SRL gains when AE were supported by analytics (Al-Shaer, 2023; Younis, 2024).

Strengths: SRL integrates cognitive, metacognitive, motivational, and behavioral dimensions, fostering resilience, autonomy, and effective time management (Zimmerman, 2002; Panadero, 2017).

Challenges: Difficulties in reliable measurement, fragmented models, underexplored digital applications, and limited regional research remain barriers (Pintrich, 2000; Al-Shaer, 2023).

Trends and gaps: Key directions include analytics-supported SRL, emotion regulation in digital learning (Zheng et al., 2021), AI-driven reflective prompts (Younis, 2024), and expansion beyond Western contexts. However, tripartite integration of LAD, AE, and SRL remains absent, leaving learners with fragmented support.

D. Dual Studies (LAD–SRL, LAD–AE, AE–SRL):

Research has largely examined LAD, AE, and SRL in pairs rather than as a unified framework. These dual studies reveal partial synergies but also systemic gaps.

- LAD–SRL: Dashboards enhance reflection and monitoring by visualizing goals, progress, and outcomes (Jivet et al., 2018; Matcha et al., 2019). Personalized dashboards improved SRL in Arab contexts (Al-Shaer, 2023; Elmabaredy & Gencel, 2024). Yet, most remain descriptive, offering awareness but lacking adaptive engines.
- LAD–AE: In adaptive platforms, dashboards act as data pipelines that inform personalization (Tseng et al., 2020; Vykopal et al., 2022). However, SRL is seldom treated as a deliberate outcome. Thus, LAD–AE systems support technical adaptation but fail to empower learners as self-regulated agents.
- AE–SRL: Adaptive systems foster SRL by embedding scaffolds and pacing mechanisms. Studies show instructor feedback and adaptive prompts influence learners' reflection and emotion regulation (Zheng et al., 2021; Panadero, 2017). Arab studies confirmed improvements in autonomy and time management when AE were analytics-informed (Al-Shaer, 2023; Younis, 2024). Yet, the absence of LAD weakens visualization and metacognitive scaffolds.

Table 1: *The analytical relationship between the three components*

Relationship	Interpretation
LAD ↔ AE	LAD represents a source of raw data that the environment uses to adjust content and courses according to the learner's needs.
LAD ↔ SRL	LAD contributes to raising learner self-awareness and enables them to monitor and improve performance based on quantitative and qualitative indicators.
AE↔SRL	The Adaptive environment provides the pedagogical support needed to develop self-regulation Learning through personalized activities, intelligent feedback, and customizable resources.

E. Comparative Synthesis:

The dual studies reveal partial synergies but confirm systemic gaps:

- LAD–SRL: Awareness but little adaptation.
- LAD–AE: Personalization without SR scaffolds.
- AE–SRL: Regulation without analytics support.

Learners thus experience fragmented ecosystems, analytics without adaptation, adaptation without regulation, or regulation without analytics.

Table 2: *Research gap between LAD, AE, and SRL.*

Study	Study Focus	LAD	AE	SRL	Tripartite Integration	Notes
Jivet et al., 2018	Designing an LAD to support SRL using visual indicators.	✓	✗	✓	✗	It focuses on visual cues without adaptive decision support or a personalized environment.
Matcha et al., 2019	An interactive LAD to stimulate SRL and provide feedback.	✓	✗	✓	✗	It does not include a true adaptive learning environment, merely dashboards.
Zheng et al., 2021	Analyzing the relationship between LAD and SRL in specific contexts.	✓	✓	✓	✗	It emphasizes the importance of the relationship, but without in-depth field study or integrated application models.
Vykopal et al., 2022	Designing an adaptive smart environment to customize practical training in cybersecurity.	✓	✓	✗	✗	It focuses on personalization and skill fit without targeting SRL as an independent skill.
Martha et al., 2023	Supporting SRL and CRL through metacognition and motivation factors.	✗	✗	✓	✗	It focuses on supporting variables without visual analysis tools or LAD guidance.

Study	Study Focus	LAD	AE	SRL	Tripartite Integration	Notes
Al-Shaer, 2023	AE with analytics for SRL	✓	✓	✓	✗	Regional evidence of dual integration, but not tripartite.
Elmabaredy & Gencel, 2024	Integrating SRL into Moodle platforms and its impact on achievement.	✗	✓	✓	✗	It does not employ LAD tools; the study focuses solely on achievement impact.
Younis, 2024	Adaptive environments with ChatGPT	✗	✓	✓	✗	Showed AE–SRL synergy, LAD missing.

Overall, evidence highlights fragmented ecosystems—analytics without adaptation, adaptation without regulation, or regulation without analytics—underscoring the need for a comprehensive tripartite model.

F. Theoretical Synthesis

Despite progress, the three-pronged integration of LAD, AE, and SRL remains absent in both theory and practice. LADs have evolved from descriptive to predictive tools (Matcha et al., 2019; Elmabaredy, & Gencel, 2024), AE have demonstrated their customizability (Tseng et al., 2020), and the importance of self-adaptive learning is widely recognized (Zimmerman, 2002; Panadero, 2017). However, none of these have been fully applied together.

This paper addresses the current gap by integrating:

- LAD as analytical mirrors.
- AE as adaptive drivers.
- SRL as pedagogical anchors.

This cycle—Data → Analytics → Adaptation → Self-Regulation Learning → New Data—connects descriptive and prescriptive functions, enriches learner models, and fosters learner-centered, intelligent ecosystems (Roll and Winn, 2015; Yunus, 2024).

The reviewed literature highlights significant progress across LAD, AE, and SRL, yet persistent fragmentation remains. This gap motivates the current study, which proposes a unified conceptual framework to integrate the three dimensions. The next section explains the methodology employed to construct and validate this framework.

7- Methodology

A.Research Design

This study adopts a conceptual–analytical review methodology, appropriate for developing frameworks in interdisciplinary domains where empirical integration is scarce (Snyder, 2019). Unlike systematic reviews focused on aggregating results, the conceptual–analytical approach synthesizes theoretical constructs, empirical evidence, and design principles. This is particularly suited to bridging the three domains of LAD, AE, and SRL, which have rarely been examined together.

B.Sources of Literature

A multi-source strategy was employed to capture both global and regional perspectives:

- Google Scholar, IEEE, ERIC, SPRINGER.
- Regional databases to include Arabic-language research.

This approach ensured coverage of recent international advances and local contextual relevance.

C.Inclusion and Exclusion Criteria

To ensure rigor, explicit criteria were applied:

Inclusion:

- Studies published between 2019–2024.
- Peer-reviewed articles, conference papers, or dissertations.
- Explicit reference to LAD, AE, or SRL.
- English or Arabic publications.
- Exclusion:
- Non-scholarly sources (blogs, reports).
- Studies lacking methodological transparency.
- Papers on LMS technology without analytics, adaptation, or regulation.

From an initial pool of 130 studies, 50 were retained after full-text screening.

D. Analytical Procedure (Thematic Coding)

Thematic coding was conducted in three iterative stages. First, codes were assigned to capture recurring constructs such as “LAD as cognitive scaffolds,” “AE for adaptive sequencing,” and “SRL goal-setting supports.” Second, codes were cross-compared across studies to identify convergences and divergences. Third, the codes were synthesized into higher-order categories, which were then mapped onto the proposed conceptual framework. This ensured that the model was not only theoretically grounded but also systematically derived from existing evidence.

The review employed thematic coding (Braun & Clarke, 2006) to extract insights across domains:

- Familiarization: Reading and annotating included studies.
- Initial coding: Tags such as “LAD for visualization,” “AE for personalization,” “SRL scaffolds.”
- Theme generation: Grouping codes into themes, e.g., “LAD as cognitive instruments,” “adaptive personalization,” “integration gaps.”
- Refinement: Ensuring themes aligned with research questions.

This process enabled systematic comparison across LAD, AE, and SRL traditions and highlighted integration opportunities.

E. Model Development

Based on the thematic presentation, the conceptual framework was developed through iterative mapping:

- LAD functions (monitoring, reflection, prediction) were aligned with SRL phases (forethought, performance, reflection).
- AE features (personalization, pacing, scaffolding) were positioned to act upon LAD outputs and reinforce SRL processes.
- Bidirectional relationships (LAD ↔ AE ↔ SRL) were designed to ensure continuous feedback and self-sustaining regulation.

The framework thus emerged conceptually from triangulated literature rather than empirical experimentation.

F. Validation Procedures

To enhance trustworthiness, validation followed a Delphi method:

- The model was presented to seven judges and educational technology experts.
- Experts reviewed the model for clarity, feasibility, and pedagogical alignment.
- Consensus (≥80% agreement) was achieved regarding the core framework components.

G. Ethical Considerations

As the study is conceptual and literature-based, no direct participants were involved. For the Delphi validation, ethical standards were followed: informed consent from experts, and adherence to institutional review protocols.

While the present study is conceptual in nature, it sets the foundation for future empirical validation. A suggested next step is a design-based research implementation within real LMS platforms, where LAD plugins will be tested for their effectiveness in fostering SRL skills. Data will be collected using mixed methods- log data, performance assessments, and learner surveys- to triangulate outcomes such as persistence, retention, and self-regulation Learning growth.

8- Results and Discussion

The integration of LAD, AE, and SRL generates a comprehensive framework for designing learner-centered intelligent systems. This section presents a clear conceptual framework for integrating the three components, analyzes the dual and triangular relationships, locates the model within previous research, and discusses its pedagogical and technological implications.

A. The Proposed Conceptual Framework:

The proposed conceptual framework operates as a recursive cyclical model, where LAD, AE, and SRL operate in a continuous loop:

- Data Collection: LAD capture learners' cognitive, behavioral, and interactional data in real time.
- Data Interpretation: AE process data through algorithms to detect needs and adapt strategies.
- Personalized Response: Content, pacing, or scaffolds are tailored to individual profiles.

- SRL Activation: Personalized feedback stimulates goal adjustment, monitoring, and reflection.
- Behavioral Adjustment: Learners refine strategies in response to adaptive support.
- Loop Completion: New behaviors feed LAD, restarting the cycle.

This model represents a closed-loop ecosystem: (data → analytics → adaptation → self-regulation learning → new data), promoting sustainable learner development.

B. Integrating LAD, AE, and SRL: A Tripartite Model:

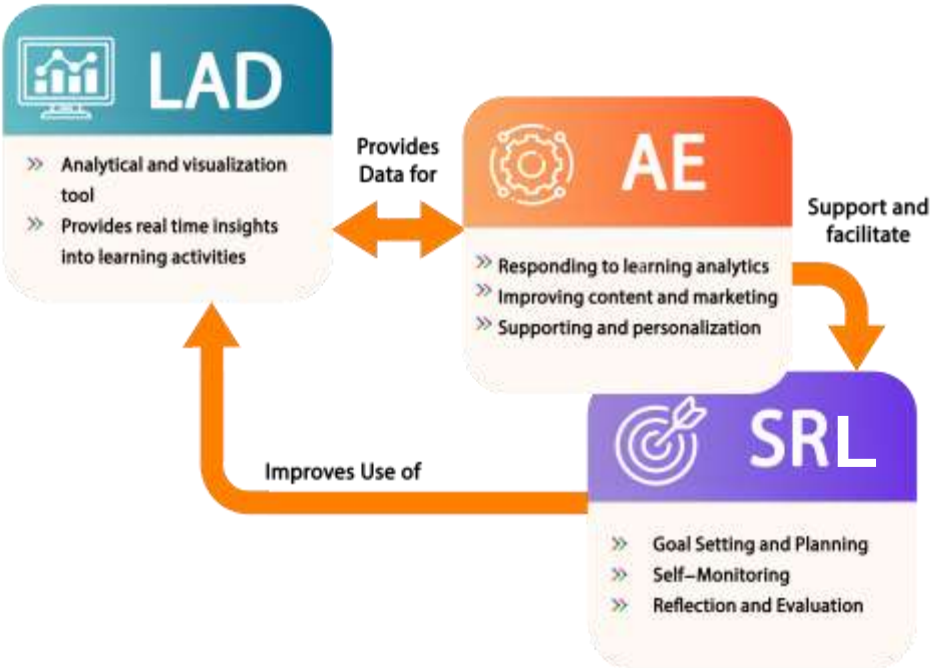
When combined, LAD, AE, and SRL form a coherent tripartite pedagogical architecture. Each component assumes a distinct yet interdependent role:

- LAD provide visibility and analytics by transforming raw learner data into actionable insights.
- AE translate these insights into adaptive pathways, tailoring content, scaffolds, and pacing to individual learner profiles.
- SRL ensures that learners actively engage with feedback, exercising goal-setting, monitoring, and reflection.

This synergy transforms LAD from static reporting tools into cognitive instruments, AE from personalization engines into responsive learning ecosystems, and SRL from an incidental by-product into a deliberate pedagogical outcome.

Figure 1

Conceptual framework for the relationship between LAD, AE, and SRL.



As shown in Figure 1, the model works as a self-generating loop to operate a closed cycle:

1. Dashboards provide data for adaptive mechanisms.
2. Adaptive environments scaffold regulatory processes.
3. Learners' regulatory behaviors feed new data back into dashboards.

Unlike dual studies that reveal only partial synergies (e.g., LAD–SRL or AE–SRL), this tripartite integration addresses the fragmentation identified in earlier literature. It ensures that analytics, adaptation, and regulation reinforce one another in a continuous loop, thereby enabling intelligent, learner-centered ecosystems that are data-driven, adaptive, and self-sustaining.

C. Alignment with Previous Studies:

The framework both aligns with and extends prior research:

- Builds on Jivet et al. (2018), who stressed LAD for SRL, by embedding them in AE.
- Extends Vykopal et al. (2022), were LAD informed AE adaptation, by adding SRL as an intentional outcome.
- Echoes Al-Shaer (2023) and Younis (2024), who found AE foster SRL, but incorporates LAD to visualize regulation.

This synthesis shows no prior work has systematically integrated all three elements into one framework.

D. Educational and Technological Implications:

Pedagogical Benefits:

- Autonomy: Learners are empowered to self-monitor and set goals with LAD feedback.
- Metacognitive scaffolding: Adaptive prompts and reflective dashboards strengthen SRL.
- Reduced dropout: Integration helps identify at-risk learners earlier (OECD, 2022).

Technological Benefits:

- Interoperability: LAD data enrich AE learner models with fine-grained analytics.
- Precision personalization: Adaptive interventions become more targeted and responsive.
- Scalability: The model can be embedded into major learning management systems (e.g., Moodle, Blackboard Ultra).

E. Practical Strengths of the Framework:

The model contributes theoretically and practically to:

- Structural integration: Aligns analytics and adaptation with pedagogical regulation.
- Flexibility: Applicable across disciplines and adaptable to different learner needs.
- Scalability: Usable in both small courses and large-scale MOOCs.
- Policy relevance: It aligns with global priorities and international trends, which emphasize artificial intelligence and analytics to achieve student success.

F. Critical Reflection

Despite its promises, the framework faces challenges:

- Technical requirements: Robust infrastructure and interoperability are needed.
- Faculty training: Instructors must learn to interpret LAD data and scaffold SRL effectively.

- Ethical safeguards: Transparency, privacy, and protection from algorithmic bias remain critical (Schumacher & Ifenthaler, 2018).

Addressing these challenges is essential for ensuring the framework's feasibility, ethical soundness, and practical viability.

Unlike previous dual-integration approaches (e.g., LAD–SRL in Jivet et al., 2018, or LAD–AE in Vykopal et al., 2022), the proposed framework advances originality by systematically embedding SRL as a deliberate outcome rather than an incidental by-product. It also reframes LAD from static reporting tools into dynamic cognitive instruments and elevates AE from personalization engines into responsive pedagogical ecosystems.

9- Recommendations

A. Recommendations for Researchers:

- Empirical validation: Move beyond conceptual theorization by conducting pilot and large-scale empirical studies that test the proposed framework in authentic contexts such as higher education, vocational training, and online systems.
- Examine diverse outcomes: Explore how LAD–AE–SRL integration influences not only academic achievement but also retention, motivation, and higher-order thinking (reflection, synthesis).
- Design-based research: Employ iterative design-based experiments to refine dashboard prototypes and adaptive features, ensuring alignment with generative learning theories.
- Cross-cultural expansion: Investigate cultural and institutional variables, especially in Arab contexts, to understand how they mediate the framework's effectiveness.

B. Guidelines for Educational Practice:

- Embed LAD into LMS architecture: Treat dashboards as core decision-support features rather than add-on reporting tools, ensuring real-time utility for learners and instructors.
- User-centered visualization: Prioritize clarity, interactivity, and interpretability. Well-designed dashboards can stimulate SRL by triggering reflection, planning, and strategy adjustment.

- Capacity-building programs: Provide structured training for educators and learners to develop data literacy and metacognitive awareness, focusing on interpreting indicators and translating them into actionable strategies.
- Curriculum integration: Instructional designers should embed SRL principles directly into course design, integrating LAD-informed scaffolds, adaptive sequencing, and reflective prompts.

C. Practical Implementation Plan in LMS

To operationalize the proposed framework, institutions can adopt a staged plan within platforms such as Moodle or Blackboard Ultra:

1. Preparation: Define SRL-related objectives and select dashboard indicators (e.g., time-on-task, engagement, completion rates).
2. Dashboard integration: Develop or customize LAD plugins ensuring bi-directional data exchange with adaptive engines.
3. Pilot implementation: Apply the integrated model in selected courses, where LAD generate adaptive recommendations and scaffolds.
4. Evaluation: Gather learner feedback, track SRL-related outcomes, and iteratively refine the framework.

This phased approach ensures technical feasibility and pedagogical coherence, aligning the framework with both institutional goals and learners' self-regulation needs.

10- Conclusion

The originality of this study lies in providing the first coherent tripartite model that fully integrates LAD, AE, and SRL into a closed feedback cycle. This originality extends beyond incremental improvements and establishes a new theoretical and practical paradigm in adaptive, data-driven learning.

This study proposes an integrated conceptual framework, a tripartite framework that integrates LAD, AE, and SRL. This model advances previous work by going beyond descriptive dashboards to create a cyclical system where data, analytics, adaptation, and regulation are enhanced. The LAD functions of monitoring, prediction, and reflection align with the SRL phases of precontemplation, performance, and reflection, and are channeled through AE mechanisms to provide individualized and timely support structures.

This study makes a theoretical and practical contribution. Theoretically, it presents the coherent framework that combines active learning (LAD), advance learning (AE), and self-regulated learning (SRL) into a single feedback structure, expanding the scope of previous dual integrations. In practice, it provides practical guidance for the design of LMS and educational practice, using dashboards as decision-support tools, defining LAD-AE data streams, and integrating self-regulation learning (SRL) pillars into daily learning activities. Pedagogical implications include enhancing autonomy, enabling early identification of at-risk learners, and fostering reflective practice. Technological implications highlight the need for interconnected data pipelines and improved learner models that capture behavioral, cognitive, and affective indicators, shifting institutions from static reports to ethically guided personalization.

Future Work: Future research should address three critical directions: (a) empirical validation of the framework within authentic LMS contexts to overcome the descriptive limitations of current dashboards; (b) longitudinal studies that measure the impact of LAD-AE-SRL integration on persistence and higher-order thinking skills, addressing the gap in short-term experimental studies; and (c) design-based research to co-develop adaptive dashboards with practitioners, mitigating the common limitation of overly technical, non-pedagogical systems.

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