Data-Driven Adaptive Learning Management: A Decision-Making Model

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Abstract:
Adaptive learning has gained broad traction in higher education, yet its practical impact remains uneven. This paper argues that the root cause is conceptual rather than technological: adaptive learning continues to be treated as a tool for individual-level personalisation, whilst its role as a process embedded within educational management is largely overlooked. To bridge this gap, the study proposes a model of adaptive educational control that reconceptualises adaptive learning as a multi-level feedback system. The model integrates data collection, analysis, decision-making, intervention, and evaluation across four nested levels – learner, instructor, course, and – a institution. By introducing an explicit decision-making layer and incorporating evaluation-driven redesign, the proposed framework transforms adaptive learning from a predictive pipeline into a coordinated system of data-informed educational governance.

Keywords: adaptive learning, educational systems management, decision-making, decision support systems, learning analytics, socio-technical systems, higher education, control loop, data analytics, digital education

1. Introduction

Adaptive learning has become one of the central elements in the digital transformation of higher education. The idea at its core is deceptively simple: instructional systems should adjust content, pacing, and feedback in response to how learners actually behave. Rapid advances in artificial intelligence and learning analytics have substantially expanded what such systems can do, opening a path – at least in theory – from static, uniform course delivery towards more flexible and individually oriented learning environments [1]. The empirical picture, however, turns out to be more complicated than the promise suggests. Meta-analyses of intelligent tutoring systems show that they tend to outperform conventional large-group instruction and, in certain configurations, approach the effectiveness of one-to-one human tutoring [2]. Yet the magnitude of these effects is heavily shaped by context: the quality of pedagogical design, the degree of alignment between assessment tasks and learning activities, and the characteristics of the students themselves [3]. Studies of adaptive platforms in higher education paint a similarly mixed picture – meaningful gains in performance and engagement under some conditions [4, 5], but notable variation in outcomes across disciplines and student cohorts. In some cases, adaptive systems appear to benefit already high-performing students disproportionately, which raises an uncomfortable question about the possible amplification of existing educational inequalities [6, 7].

These findings point to a conclusion that frames the remainder of this paper: the effectiveness of adaptive learning depends not only on technological sophistication but also on how these systems are woven into the fabric of educational practice. The dominant paradigm remains focused on personalisation at the individual learner level, with limited attention to how adaptive processes interact with pedagogical decisions, course design, and institutional governance. It is precisely this gap that the model of adaptive educational control proposed below seeks to address – a framework that reconceptualises adaptive learning as a system-level process, designed to support coordinated adaptation across multiple tiers of the educational system.

2. Literature Review

Research on adaptive learning in higher education has developed largely within a personalisation paradigm: instructional systems dynamically adjust content, sequencing, and feedback on the basis of learner characteristics [1, 8]. In practice, this has been realised primarily through learning management systems augmented with adaptive modules that incorporate learner profiling, content adaptation, and feedback mechanisms [9, 10]. Recent advances in machine learning and natural language processing have broadened these capabilities, enabling more accurate performance prediction, optimisation of learning pathways, and automated content recommendations [11, 12].

For all this technical progress, however, a number of persistent difficulties remain. In practice, adaptive systems tend to be tied to a single platform, integrate poorly with others, and depend heavily on the conditions in which they are deployed – all of which hinders their scaling and embedding within institutional infrastructure [5, 13]. Problems of algorithmic bias and the uneven readiness of higher education institutions for change do little to encourage wider adoption [12, 14, 15, 16]. There is, however, a more fundamental difficulty – one that concerns the gap between analytics and actual action. Adaptive systems accumulate vast quantities of data and generate predictions, yet they offer little help in determining what to do with those predictions, how to translate them into concrete pedagogical steps or managerial decisions. Analytics, by and large, serves as an instrument of observation and forecasting rather than a means of organising purposeful intervention [14]. As a result, adaptive learning remains confined within the boundaries of an individual course or the work with a particular student, with scarcely any connection to educational governance at the institutional level – a fragmentation that plainly points to the need for a systemic approach.

3. Problem Statement

The limitations reviewed above converge on a single structural gap: the absence of a coherent mechanism linking analytical outputs to educational decision-making and its implementation [17–19]. Existing systems generate predictions, populate analytics dashboards, and trigger alerts, yet they provide minimal support for converting these outputs into decisions that can be acted upon – let alone for evaluating whether the actions taken have achieved their intended results [14, 15]. The assumption that adaptive learning can function as a fully automated feedback loop – data in, intervention out – does not withstand confrontation with the complexity of real educational settings, where consequential decisions depend on contextual understanding, professional judgement, and the interplay among multiple stakeholders [18, 20, 21]. Bridging this gap requires a shift in approach – from a focus on data towards a focus on decision-making capable of supporting coordinated action across the multiple levels at which higher education actually operates [19, 22].

4. Theoretical Foundations

The notion of adaptive learning as a control system has its roots in cybernetics. Pask [23] was amongst the first to formalise teaching in control-engineering terms [23, 24], treating the learner as a dynamic system whose development is governed by continuous alignment between instructional input and learner state. In contemporary scholarship, these cybernetic ideas have found their most prominent expression in Clow's learning analytics cycle [17] – a feedback loop in which learners generate data, data are transformed into metrics, and the resulting insights are fed back into the learning process through intervention. The key contribution of this model is its insistence on "closing the loop": data collection and analysis yield little if the return channel to learners and instructors is absent or poorly organised [17, 18, 25]. Sailer and colleagues [26] developed this idea into a structured closed-loop model, yet their analysis revealed a telling imbalance: predictive capabilities have advanced considerably, whilst the capacity to translate analytical outputs into meaningful pedagogical action has not kept pace [16, 26, 27]. Research confirms that many analytics systems are effective at identifying behavioural patterns but encounter serious difficulties when it comes to generating context-sensitive and practically actionable interventions [15, 27–30]. In parallel, there is a growing recognition that the human element in adaptive systems cannot be eliminated. Human-in-the-loop approaches maintain that analytics should complement rather than supplant professional judgement [21, 31–33], and empirical evidence supports this position: effective adaptation depends on the interplay between analytical outputs and human interpretation.

Taken together, these lines of research lead to a conclusion: adaptive learning is most productively understood as a sociotechnical system [22, 34, 35] operating through feedback mechanisms. The theoretical foundations of closed-loop learning are well established; what is lacking is the integration of decision-making and intervention as explicit, structured components of the cycle [36–38]. It is precisely this incompleteness that served as the starting point for the model proposed in this paper.

5. Proposed Model of Adaptive Educational Control

5.1. Conceptual Overview

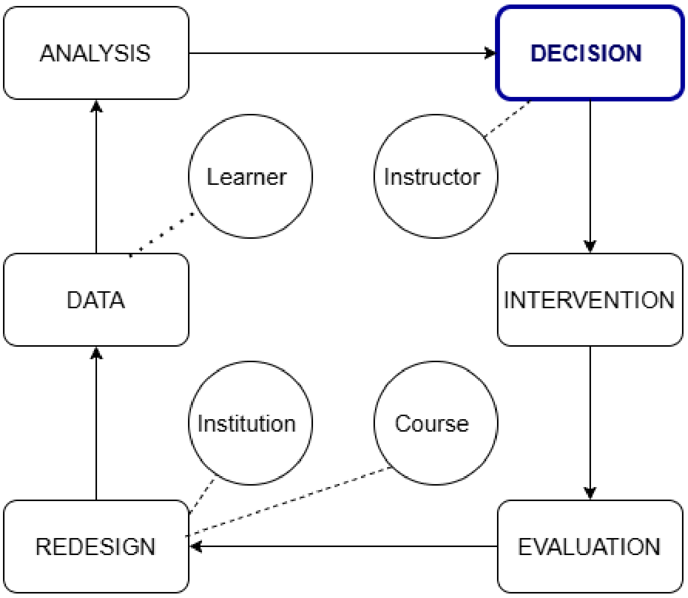
The model addresses two key limitations that the preceding analysis brought into sharpest relief: the absence of a structured decision-making layer between analysis and response, and the incomplete realisation of feedback loops that would allow systems to learn from the outcomes of their own interventions. Rather than treating adaptive learning as a collection of isolated personalisation mechanisms, the model reconceptualises adaptation as a system-level process driven by feedback. A central assumption is that adaptation in education does not occur solely at the level of the individual learner. It arises through interactions that cut across multiple layers – instructors exercise pedagogical judgement, course structures define what is possible, institutional processes allocate resources. Effective adaptation, therefore, requires coordination between analytical insights and decision-making at each of these levels.

Two key propositions follow from this premise. First, the model introduces a decision-making layer between analytical outputs and intervention – a layer that exists because educational decisions require contextual interpretation, the weighing of competing factors, and professional judgement that cannot be fully automated. Second, it embeds the entire process within a continuous feedback cycle in which the outcomes of interventions are systematically evaluated and used to refine both analytical models and decision-making strategies. Together, these extensions move the field away from a predominantly predictive paradigm towards a model oriented around managerial decision-making.

5.2. Definition and Description

The model is conceived as a multi-level feedback system [24, 39] comprising six interrelated components within a continuous adaptive loop (Fig. 1).

Figure 1: Data-driven adaptive learning control cycle



Data collection captures behavioural, performance, and contextual information from the learning environment [40, 41]. This stage has reached a relative degree of maturity, although the data gathered still tend to be scattered across systems with weak integration at the organisational level.

At the analytical processing stage, raw data are converted into material that can be worked with: performance indicators [29, 42], risk assessments, and predictive models. Here, however, a characteristic imbalance emerges – systems are reasonably good at predicting what may happen, but offer virtually no guidance on what to do about it [28, 43]. It is this asymmetry that creates a dependency on how well the next stage is organised.

Decision-making occupies a central place in the model. Conventional adaptive systems proceed from the assumption that an analytical output itself triggers a response – a prediction appears, action follows. The proposed model works differently: it separates computation from its interpretation, and this is not a theoretical indulgence. Study after study records that it is precisely at this juncture that most systems break down: instructors and academic administrators do not react to signals mechanically – they evaluate them, weigh them against alternatives, draw on their own experience, and only then decide whether to intervene and how [20].

Once a decision has been taken, the turn comes for intervention – the carrying out of concrete actions: targeted feedback to a student, a change in the mode of content delivery, additional support, restructuring of a course, or organisational measures at the institutional level [30, 44]. The model deliberately expands the narrow repertoire of existing systems to encompass both automated and human-mediated responses.

Evaluation determines the results of interventions through measurable indicators. Its role is of great importance, yet it remains one of the least developed stages: few studies rigorously measure the effects of interventions, and fewer still systematically feed results back into the system [16, 45, 46].

Course redesign closes the loop by channelling evaluation results into system improvement – recalibrating models, adjusting decision rules, and revising strategies [38, 47]. By including redesign as a structural component, the model transforms adaptive learning from a reactive process into a system capable of continuous self-improvement.

These components form an interconnected system in which a weakness at any point diminishes the quality of the entire cycle. The evidence indicates that the two most critical junctures are the transitions from analysis to decision-making and from intervention to evaluation.

5.3. Mathematical Representation

The model can be formalised as a discrete-time feedback process operating over successive time steps $\boldsymbol{t}$.

$A_t = f(D_t, S_t)$ – analytical processing, which transforms data (***D***) and the system state (***S***) into interpretable outputs.

$I_t = \delta(A_t, S_t)$ – decision-making (***I*** – intervention), which determines whether intervention is required and what form it should take. The explicit separation of $\boldsymbol{\delta}$ (decision-making) from ***f*** (the analytical function) represents the model's most significant formal departure: it reflects the empirical reality in which educational decisions require contextual consideration that extends beyond algorithmic computation.

$O_t = g(I_t, S_t)$ – intervention outcomes, reflecting the fact that the effect depends not only on the action itself but also on the state of the system in which it is carried out.

$S_{\{t+1\}} = R(S_t, O_t)$ – redesign, which updates the system on the basis of observed outcomes.

The system state has a composite structure:

$$S_t = \left\{ S_t^{\{learner\}}, S_t^{\{instructor\}}, S_t^{\{course\}}, S_t^{\{institution\}} \right\}$$

The complete process:

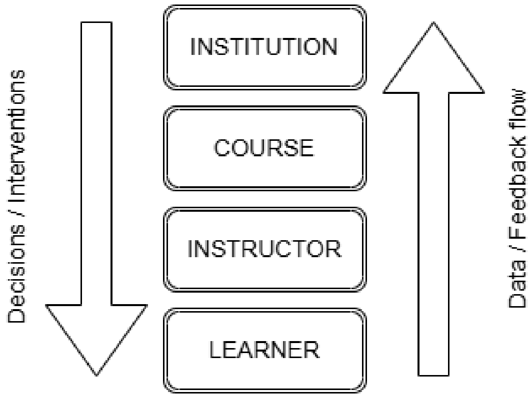
$$D_t \rightarrow A_t \rightarrow \delta \rightarrow I_t \rightarrow O_t \rightarrow S_{\{t+1\}}$$

The key formal distinction lies in the explicit separation of four functions that conventional systems tend to conflate: analytical inference (***f***), decision-making ($\boldsymbol{\delta}$), intervention effects (***g***), and system adaptation (***R***).

5.4. Multi-Level Structure of the Model

What most fundamentally distinguishes the model is its multi-level architecture, reflecting consistent evidence that learning outcomes are shaped not by individual behaviour alone but by its interaction with teaching practices, course design, and institutional conditions (Fig. 2).

Figure 2. Hierarchy of adaptive learning management levels



At the learner level, the model provides personalised feedback and the construction of learning trajectories. At the instructor level, it supports pedagogical decisions that are impossible without first-hand knowledge of the audience – who is falling behind in the group, where attention is lost, which material causes difficulties. At the course level, it opens the way for structural changes: revising the sequence of topics, redistributing workload across weeks, and adjusting assessment formats. At the institutional level, it assists in deciding where to direct resources and how to adjust educational policy.

Crucially, these levels do not exist in isolation. They are interwoven. If, for instance, a group of students displays a systematic problem with a particular type of assignment, this may prompt the instructor to change approach. A successful solution found by the instructor may then form the basis for redesigning the entire course. And if the same problem surfaces across several courses simultaneously, it becomes a signal for the institution: perhaps the issue lies in the curriculum or in a shortage of resources. Feedback operates from the top down as well: decisions at the institutional level alter the conditions in which instructors work and students learn. The cycle, in other words, is not contained within a single layer – it runs through all of them.

5.5. Key Contribution of the Model

The model makes three specific contributions to the problem identified above. First, establishing decision-making as a separate layer gives instructors and administrators a legitimate place within the adaptive cycle – their contextual understanding and professional experience cease to be something external to the system and become a working element of it. Second, the multi-level design links actions across different tiers – an intervention at the level of a particular student or course does not hang in a vacuum but is related to what is happening at the departmental or institutional level. Third, the built-in mechanism for review on the basis of actual results prevents the system from running indefinitely on autopilot – it is compelled to verify whether what was done actually worked and to adjust itself, rather than relying on assumptions that no one has tested.

In practical terms, the model can be implemented through staged adoption at the institutional level: beginning with learner-level analytics integrated into the existing LMS infrastructure, gradually incorporating decision-support dashboards for instructors with contextual recommendations, and ultimately extending to feedback mechanisms at the course and institutional levels coordinated through a shared data governance framework. The specific configuration will inevitably vary depending on the institutional context, but the model's layered architecture is designed for incremental adoption rather than wholesale systemic transformation.

6. Operational Logic and Implementation of the Model

The preceding sections established what the model is. The question now is how it functions in practice and where its implementation is most likely to encounter constraints.

The operational logic is fundamentally iterative: the results of each stage feed back, driving gradual improvement of the system. In practice, stages overlap and interact in ways that resist neat sequential description, yet the overall flow provides an organising axis. What matters operationally is not the individual stages – these have already been defined above – but the dynamics of their interaction.

Two transitions prove to be the most vulnerable, serving as critical points of failure (Fig. 3).

Figure 3: Critical breakpoints in adaptive learning management

DATA → ANALYSIS → X → DECISION → INTERVENTION → X → EVALUATION

X - Interpretation Gap

The first is the transition from analysis to decision-making. Analytical outputs arrive, but the infrastructure for their contextual interpretation is largely absent. Instructors develop understanding through interaction with data; their responses are shaped by contextual knowledge that is not captured in analytics dashboards. This transition cannot be automated. It requires institutional support – training in data interpretation, dedicated time for reflection, and clear protocols for escalating issues between levels.

The second is the transition from intervention to the evaluation of results. In the majority of cases, it is at this stage that the loop breaks. An intervention has been carried out, yet its consequences are rarely tracked and seldom with due rigour. Without systematic evaluation, the system is unable to distinguish what works from what does not, and course redesign becomes impossible.

A defining operational characteristic is the model's simultaneous functioning across each layer with different temporal rhythms. At the learner level, the cycle turns over in a matter of days. At the instructor level, pedagogical strategy evolves over weeks. At the course level, redesign operates from one semester to the next. At the institutional level, the cycle may span years. Coordinating these rhythms – rather than leaving them to run on their own – is a challenge that no existing system has adequately addressed, but one that the proposed architecture is designed to support.

7. Limitations of Adaptive Learning and Learning Analytics Systems

Existing adaptive learning systems are realised as closed-loop processes only in part. Data collection and analysis have reached a relative degree of maturity. It is at the stages of decision-making, intervention, and evaluation that the chain most frequently breaks. The gap at the intervention stage remains the most thoroughly studied and documented problem. Systems identify patterns and predict risks with reasonable competence, yet the repertoire of available responses is narrow, and there is surprisingly little evidence on which interventions actually work, for whom, and under what conditions [2–5, 8, 15]. Analytics dashboards offer a clear illustration: they make data more accessible, but their influence on actual learning outcomes remains inconsistent [14, 48].

Algorithmic bias constitutes a separate but no less significant problem. Predictive models built on historical data risk reproducing already existing inequalities, and this affects students from underrepresented groups first and foremost [49]. Attempts to mitigate bias involve trade-offs between fairness and accuracy, underscoring the limitations of fully automated decision-making. Professional and organisational factors compound the technical shortcomings. Instructor scepticism towards analytics tools [50], combined with insufficient training and institutional support, frequently leads to superficial use of data even where tools have been formally adopted [51].

These limitations grow sharper across different levels. At the instructor level, decision-making requires interpretation and resists automation [20]. At the student level, analytics-driven interventions presuppose skills of self-analysis and conscious management of one's own learning (metacognitive skills) that many learners do not yet possess [16, 45]. At the institutional level, implementation demands coordinated work across academic, administrative, and technical units – a challenge that researchers have characterised as a "wicked problem" [37] – whilst most applications remain focused on individual learners rather than on system-level processes [52].

These persistent limitations strengthen the case for models that treat decision-making as an explicitly designated structural component, rather than as something that ought to emerge of its own accord in the course of analytical work.

8. Discussion

The findings indicate that the principal limitation of current adaptive learning systems is structural rather than technological. The gap lies not in data or analytical capacity but in the mechanisms linking analytics to coordinated action.

The proposed model addresses this gap by establishing decision-making as a distinct component and extending feedback across multiple levels of the educational system. The mechanism for reviewing the system on the basis of its results plays a particularly important role: it is this that ensures genuine continuous improvement rather than mere reaction to problems that have already arisen.

The evidence consistently points to the fact that effective adaptive learning depends on the active involvement of people. Data must be interpreted, priorities weighed, context-sensitive judgements made, and for these tasks professional expertise remains indispensable. This lends support to hybrid architectures in which analytics complement professional judgement rather than attempting to replace it.

Implementing such models involves practical difficulties. Data governance needs to be improved. Instructors' analytical literacy must be deliberately cultivated. Institutional structures may require substantial restructuring to enable cross-level coordination. None of these tasks is trivial, yet the alternative – continuing to invest in predictive systems that generate insights upon which no one acts – is hardly more productive.

This work continues a line of research that views adaptive learning not as a purely technical solution but as a sociotechnical system in which data, professional judgement, and the institutional environment are inseparably linked. By bringing these elements together within a single framework, we lay the foundations for adaptive learning environments that are analytically sound, pedagogically grounded, and sustainable at the level of educational organisations.

9. Conclusion

The principal limitation of adaptive learning systems in higher education is structural rather than technological. Existing systems collect and analyse data effectively but lack coherent mechanisms for translating analytical results into coordinated educational action.

The proposed model of adaptive educational control bridges this gap in three directions: it establishes decision-making as a distinct layer between analysis and intervention, builds a multi-level architecture linking processes at the learner, instructor, course, and institutional levels, and embeds the review of the system on the basis of evaluation results as a mandatory structural element. Together, these three elements transform adaptive learning from a system oriented towards prediction into one built around decision-making and the management of the educational process.

The further development of the field requires a shift in focus from data-centred approaches towards approaches centred on decision-making. Technological progress alone is insufficient for this; professional judgement, institutional governance mechanisms, and organisational support must be purposefully built into adaptive systems. Testing the proposed model across a range of educational institutions and developing practical implementation strategies remain priorities for future research.

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