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Context-Sensitive Interpretation of Educational Events in Adaptive Learning Environments

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Abstract:
Learning analytics systems now capture substantial volumes of behavioural data, yet identical events can stand for very different learning situations depending on the discipline, the structure of the trajectory, the learner's self-regulation patterns and the temporal dynamics of the course itself. This undermines the robustness of adaptive interventions built on event-based logic. Objective: to develop a context-sensitive model for interpreting educational events in adaptive learning systems. Methods: a systems and comparative analysis, conceptual modelling, and classification of contextual modifiers, drawing on case studies from project-based learning and marketing education. Scientific novelty: an interpretive layer is formalised between event detection and intervention decision-making, and a schema "event – context – interpretation – state assessment – intervention" is proposed that accounts for disciplinary specificity, trajectory dynamics and combinations of events. Results: five groups of educational events have been identified that call for different interpretation depending on the structure of the discipline. Universal "event → intervention" logic was found to produce a substantial number of false-positive signals, particularly when reading low LMS activity and repeated attempts. Applying the model reduces these false signals and lowers the cognitive demand placed on the instructor. Practical significance: the architecture is applicable to the design of learning management systems, teacher-facing dashboards and decision support systems.

Keywords: adaptive learning systems, learning analytics, contextual interpretation, educational events, adaptive intervention, self-regulated learning, trajectory analysis, teacher-facing dashboards, educational data, context-aware analytics, digital learning environments, semantic interpretation

1. Introduction

Adaptive learning systems now lean heavily on streams of behavioural events produced inside the digital learning environment. Their staple inputs are familiar: login frequency, repeated attempts, time on task, navigation patterns, missed deadlines, assessment results and the like – the everyday digital footprint of the learner [1–4]. From this material the field builds its predictive models, its triggers for adaptive support and its dashboards for teachers. In most existing learning analytics designs, the link between event and response is a short one: a deviation is observed, a risk is inferred, a corrective action follows. The underlying assumption is that behavioural indicators carry stable meaning – that a drop in activity, on its own, says something definite about the learner. That assumption does not hold up well in practice. The same digital trace can correspond to quite different states depending on how the discipline is organised, how tightly its topics depend on one another, how the learner manages their own work, and how the wider educational activity is set up.

A telling example is repeated attempts at a task. In project-based learning they are typically part of iterative refinement – the solution settles down through successive rounds of work. In a course where each topic strictly builds on the previous one, the same pattern may instead signal cumulative confusion and a fraying trajectory. The same ambiguity surrounds low LMS activity: it can mean that the learner has dropped out of the process, or that intensive work is simply taking place beyond the platform. A semantic ambiguity emerges: events are reliably captured, but their meaning hinges on the context in which they appear. Current learning analytics systems handle this only in part. The prevailing designs are still event-centred and prediction-oriented; they catch behavioural deviations well, but have little to say about what those deviations actually mean [1, 5]. The result is a steady drip of false alarms and missed signals, particularly in mixed cohorts where learners differ in their self-regulation strategies and where disciplines have very different shapes [6–9].

Recent work has been quietly chipping away at the universal logic of event-based response. Hlosta, Zdrahal and Zendulka showed that predictive models built purely on visible traces miss a great many contextual factors that algorithms simply do not see [13]. Chen and colleagues found that information about the instructional setting markedly changes how online behaviour data should be read [11]. Saqr and López-Pernas argued that risk emerges not from any single event but from the way a trajectory unfolds over time [23, 24]. Adaptive learning systems themselves are also growing more elaborate, both organisationally and computationally. Teacher dashboards, orchestration tools and closed-loop analytics frameworks now generate a great volume of signals that must somehow be interpreted on the fly [3, 4, 14–18]. The centre of gravity is gradually shifting from straightforward event detection towards architectures built around interpretation. The dashboards meant to help teachers are themselves a source of trouble. Pozdniakov and colleagues showed that how well a teacher reads a dashboard depends rather heavily on their visualisation literacy [14]. Liu, Pozdniakov and Martinez-Maldonado traced a direct line from increasing visual complexity to rising cognitive load [15]. Lee-Cultura, Sharma and Giannakos pointed to the demands placed on teachers by multimodal dashboards, where a varied set of signals must be reconciled into a single picture [16]. A parallel strand of work – semantic and ontology-based learning analytics – is exploring how raw events might be lifted into richer representations [19–22]. Much of it, though, is concerned with interoperability and data integration on the one hand, or with the portability of predictive models on the other. The question of how educational events should actually be interpreted in context has received less formal attention.

The present study takes up that question directly. We propose a context-sensitive interpretive architecture in which events are not treated as direct triggers for action but as signals requiring semantic reading through a set of contextual modifiers. The approach reframes the standard adaptive logic – "event → intervention" – into a fuller cycle: "event → contextual interpretation → educational state → adaptive intervention". Particular weight is given to three modifiers that prove central in shaping the meaning of behavioural events: the discipline itself, the way the learner's trajectory is structured, and their habits of self-regulation.

2. Problem Statement

Contemporary adaptive learning systems mostly run on event-based logic. Platforms gather behavioural traces around the clock and convert them into predictive indicators meant to flag disengagement, instability in the learner's path, or rising risk [1–4]. In the bulk of existing designs, intervention is fired off the back of an observable event with little delay. The approach assumes that behavioural indicators carry stable meaning. The picture is far less tidy than that: identical events, depending on the circumstances in which they appear, can correspond to wholly different learner states.

The issue is particularly stark in heterogeneous learning environments, where one finds disciplines with very different shapes, varying degrees of prerequisite dependency, an assortment of self-regulation strategies, non-linear and project-based trajectories, and hybrid online–offline activity all bundled together. Take repeated attempts: behind that single signal one might find iterative refinement of a project solution, exploratory learning, collaborative correction of intermediate stages, the accumulation of difficulties, or a breakdown in the underlying knowledge structure. Low LMS activity is much the same – it can be disengagement, or it can be intensive work happening entirely off the platform. What we observe, in short, is semantically underdetermined. Existing learning analytics systems tackle this only partly. The bulk of predictive architectures remain centred on behavioural detection rather than on contextual reading of events [1, 5, 11]. The consequences are familiar: false positives, missed cases, shaky intervention logic, overloaded teachers, and models that travel badly between disciplines and courses [13–16]. Contemporary teacher dashboards make the situation worse rather than better. They pull a diverse set of indicators into a single visual surface that the instructor must keep reading on the fly [14–17] – yet they rarely provide any built-in machinery for reading those indicators in context.

Pozdniakov and colleagues have shown that a teacher's ability to read a dashboard rests heavily on their visualisation literacy and on the kind of interpretive guidance available to them [14]. Building on that, Liu, Pozdniakov and Martinez-Maldonado mapped a direct relationship between dashboard complexity and rising cognitive load [15]. Instructors, in other words, are increasingly being asked not just to monitor the learning process but to reconstruct the meaning of behavioural traces on a daily basis.

A second architectural weakness surfaces in the same analysis. Most predictive models concentrate on events rather than on trajectories. The intervention is set off by a single behaviour even though, in practice, instability typically grows out of a combination of events that develop over time [6, 23, 24]. Saqr and López-Pernas have shown that longitudinal trajectory dynamics offer steadier indicators of instability than isolated behavioural events [23], and sequential modelling work using Hidden Markov Models for risk detection points in the same direction [7]. This sets up a fundamental architectural tension: adaptive systems lean ever more heavily on event streams, while the meaning of those streams depends on contextual relationships that event-based architectures do not represent. Research in semantic and ontology-based learning analytics has been picking up this challenge, with growing interest in contextual and semantic modelling [19–22]. Much of the work, however, gravitates towards interoperability of data, semantic integration of heterogeneous sources, the portability of predictive models, or ontology-based representation of learning objects. The narrower problem – how to interpret events as part of intervention logic itself – has been left comparatively under-formalised.

Our starting premise here is simple: an event should not directly trigger a response. A decision to intervene requires an intermediate interpretive layer that reconstructs the meaning of behaviour through a set of contextual modifiers. Risk, on this view, is not a property of any single event but a context-sensitive characteristic emerging from the structure of the discipline, the way the learner's trajectory is put together, the combinations in which events arise, the learner's own self-regulation, and the temporal dynamics of behaviour. The study therefore takes on the task of building a context-sensitive interpretive architecture that turns raw events into intervention signals one can actually interpret.

3. Context-Sensitive Interpretive Architecture

3.1. General Architecture

Our architecture starts from a simple premise: events have no fixed meaning of their own and cannot, on their own, justify a response. Between the trace and the action there must sit an interpretive layer that reconstructs what a behaviour actually means in its particular setting.

Five interconnected layers make up the model (fig. 1):

$$E \rightarrow C \rightarrow I \rightarrow S \rightarrow A$$

where E is an educational event; C is the set of contextual modifiers; I is the interpretive layer; S is the educational state assessment; and A is the adaptive intervention.

In contrast to conventional event-driven designs, this model keeps detection and decision-making apart. Events are read as signals whose meaning is not yet complete; they need to be interpreted in context before any adaptive action follows.

3.2. Educational Event Layer

The first layer holds the observable events captured by the digital environment – raw traces, without any predefined meaning attached. Six categories of event sit at this level: repeated attempts, low LMS activity, missed deadlines, repeated returns to the same material, breaks in the learning trajectory, and sudden drops in assessment results.

At this stage we treat them strictly as observable phenomena. No claims about risk are made yet. This separation matters because the very same trace may correspond to different underlying processes depending on the conditions that surround it.

Repeated attempts, for instance, can mean iterative refinement, exploratory work, or a failure to grasp prerequisites. Low LMS activity can mean disengagement or simply that the work has moved elsewhere. A missed deadline might be a local hiccup or the start of a broader breakdown. The event layer, then, gathers activity – not its interpretation.

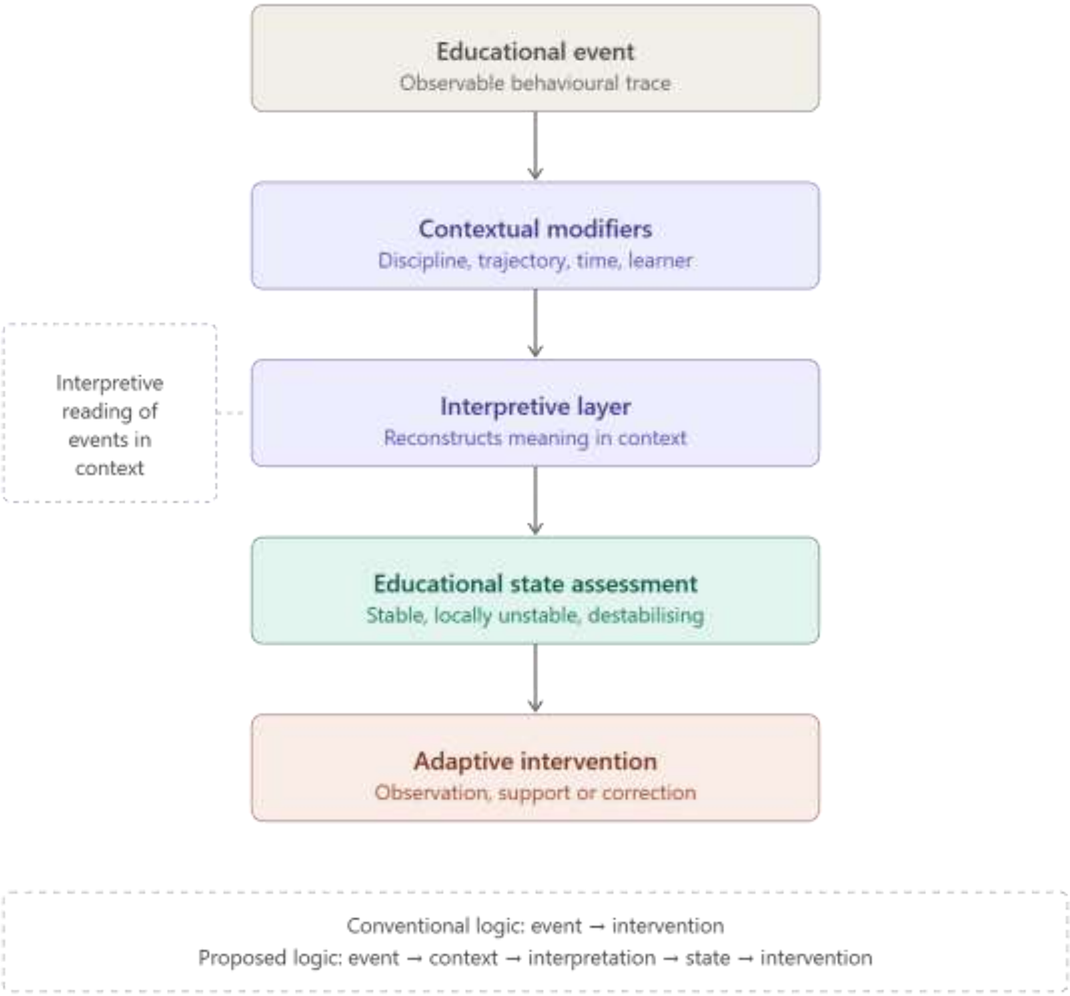

Figure 1. Context-Sensitive Interpretive Architecture

3.3. Contextual Modifier Layer

The second layer is where the contextual modifiers live – the conditions that tell us how an event should be read. The architecture sets out six such dimensions.

3.3.1. Disciplinary context

How a discipline is built shapes what a given behaviour actually signifies. Where the topics build tightly on one another, the dynamics look very different from disciplines whose work is mostly analytical or project-driven. In a project-based environment, repeated attempts usually belong to the iterative refinement of a solution. In a sequential, prerequisite-heavy course the same pattern can point to a growing pile of unresolved confusion.

3.3.2. Trajectory dependency

How we read an event also depends on where it sits within the learner's path. The architecture distinguishes events that stand alone locally from those that are structurally linked to others, and both of these from cascading disruptions that ripple through a trajectory. The distinction matters because instability tends to build up through combinations of events rather than appearing fully formed in a single deviation.

3.3.3. Temporal dynamics
Meaning also shifts with time. The same behaviour may carry quite different weight at the start of a course, during intense project work, in the run-up to a deadline, or during a period of transition between phases of study. Interpretation, accordingly, has to take into account where in the course the event occurs.

3.3.4. Self-regulated learning
Events are further filtered through the learner's own habits of self-regulation. Students with strong self-regulation often work in non-linear rhythms, draw on external resources, set their own pace and interact with the platform in irregular bursts. Low LMS activity or slow responses, in their case, need not signal anything amiss.

3.3.5. Localisation of educational activity
A large slice of learning activity often takes place beyond the platform altogether. This is especially true of project-based learning, collaborative work, analytical disciplines and hybrid course designs. The architecture therefore treats LMS activity as a partial snapshot of behaviour rather than a complete picture.

3.3.6. Event combinations
A final assumption of the architecture: instability typically grows out of combinations of events, not single indicators. Low LMS activity on its own may be quite neutral. Combine it with a missed deadline and a break in the learning trajectory, however, and the picture changes – the system is starting to wobble. Risk, on this account, is an emergent property of how events interact.

3.4. Interpretive Layer
At the heart of the architecture lies the interpretive layer itself. Its task is to turn observable traces into states that one can actually interpret. Here single events are placed in their context, contradictory signals are reconciled, combinations are read as they evolve, and meaning is reconstructed.

The layer thus mediates between what the system sees and what it decides to do. Instead of slapping an "at-risk" label on a student, the architecture assesses how stable the learning trajectory is under the prevailing conditions.

3.5. Educational State Assessment
After contextual reading, the architecture turns to assessing the learner's state. Three broad states are distinguished: a stable trajectory, one with localised instability, and one that is progressively destabilising. The state is dynamic, not fixed. A learner can move between these states depending on the accumulation of events, the effects of interventions already taken, shifts in context and the working of any recovery mechanisms.

3.6. Adaptive Intervention Layer
Only once context has been read and the learner's state assessed does the system act. It distinguishes three possible responses: observation without action, low-intensity adaptive support, and active corrective intervention.

This graded response cuts down on false positives and prevents the over-saturation of intervention often seen in mixed cohorts. Instead of reacting to every deviation, the system targets patterns of instability that are meaningful in context. The result is a shift from event-reactive to context-sensitive regulation.

The architecture, in this light, recasts adaptive systems not as predictive event-processors but as interpretive decision-makers operating under semantic uncertainty.

4. Comparative Interpretation of Educational Events

To put the architecture to the test, we compare how identical events are interpreted across two settings: project-based learning and marketing education. The two were chosen because they differ markedly in trajectory structure, in how strongly topics depend on one another, and in how educational activity is organised. The comparison shows that the same trace can call for very different intervention logic depending on the discipline (table 1).

Table 1. Comparative Interpretation of Educational Events Across Disciplinary Contexts

Educational event	Project-based learning	Marketing education
Repeated returns to the same material	Refining the project structure or iterative reworking of a solution	Working analytically through the material
Repeated attempts at a task	Adjusting the project solution or breakdown of stage-by-stage progression	Refining the analytical argument
Missed deadline	Risk of destabilising the wider trajectory of the project	Local timing slip with limited downstream impact
Low LMS activity	Work taking place off the platform, or loss of control over the project	Independent analytical work outside the LMS
Sudden drop in assessment results	Accumulating errors in the project structure	Effect of task difficulty or a change in the assignment format

4.1. Repeated attempts

Few behavioural indicators are as ambiguous as repeated attempts. Conventional event-based designs read them as a sign of instability or insufficient mastery; the data say something more nuanced.

In project-based learning, repeated attempts are typically a normal part of iterative refinement. Learners rework the project's architecture, change their implementation logic, revise intermediate solutions, redistribute tasks within the group and rebuild the structure of their presentation. Here, repeated attempts more often signal productive work than trouble – commonly associated with exploratory behaviour, gradual stabilisation of a solution, collaborative correction and adaptive restructuring of the project.

Triggering an aggressive response on attempt frequency alone is therefore liable to interrupt productive learning. In a tightly structured, prerequisite-heavy course the same behaviour reads very differently – it can point to unresolved conceptual gaps, cumulative misunderstanding and creeping disruption of the trajectory.

The same event, in short, carries fundamentally different meaning depending on how the trajectory is built.

4.2. Low LMS activity

Low LMS activity is similarly slippery. Conventional predictive systems take reduced platform interaction as disengagement; that reading wears thin in hybrid and project-oriented courses.

In project-based settings, a great deal of learning happens off the platform – in collaborative coordination of the project, in external development environments, in analytical work with outside resources, in offline group meetings and in distributed project communication. Low LMS activity can therefore coexist with quite stable, even intensive, engagement.

Three distinct interpretations stand out: genuine disengagement, externalised activity, and autonomous self-regulated learning. These produce strikingly similar LMS traces yet correspond to very different underlying situations. For predictive architectures that rely solely on platform-based indicators, this is a serious limitation.

4.3. Missed deadlines

The weight of a missed deadline likewise depends on how the course is built. In project-based trajectories a late submission tends to cause cascading instability because the project's stages depend on one another – a delay at one stage can throw off subsequent phases, destabilise coordination, break the synchronisation of project groups and leave a string of dependencies unresolved.

In such cases, a missed deadline is a high-impact event in the life of the trajectory. Marketing education, by contrast, has a more flexible architecture. A late submission there typically remains a local matter and does not bring the wider trajectory down with it. Despite identical observable events, the urgency of intervention differs considerably between these contexts.

4.4. Event combinations

The study makes the case that instability rarely springs from any single event. It develops through combinations of events that interact and unfold dynamically over time.

Low LMS activity on its own is usually neutral. Repeated attempts on their own often correspond to productive refinement. An isolated missed deadline may cause only local turbulence. Their combination, however, changes the picture considerably.

One configuration in particular was repeatedly tied to mounting trajectory instability: low LMS activity together with a missed deadline, repeated unsuccessful attempts, and an absence of any visible signs of progress. No single indicator on this list reliably predicted instability on its own – the risk emerged from how these indicators came together in context.

This supports the architecture's central claim: meaning is generated not by events as such, but by their configuration within an evolving trajectory.

4.5. Implications for adaptive intervention

The comparison exposes the limits of universal event-based intervention logic. Systems built on single behavioural indicators tend to overproduce false positives, misclassify productive learning behaviour as trouble, produce uneven intervention density and add to teachers' cognitive load.

The context-sensitive architecture delivers a different strategy. Instead of jumping at deviations, its intervention logic weighs contextual conditions, the structure of the trajectory, temporal dynamics, the combination of events at play and the learner's self-regulation patterns. Adaptive intervention thereby becomes selective rather than reactive (fig. 2).

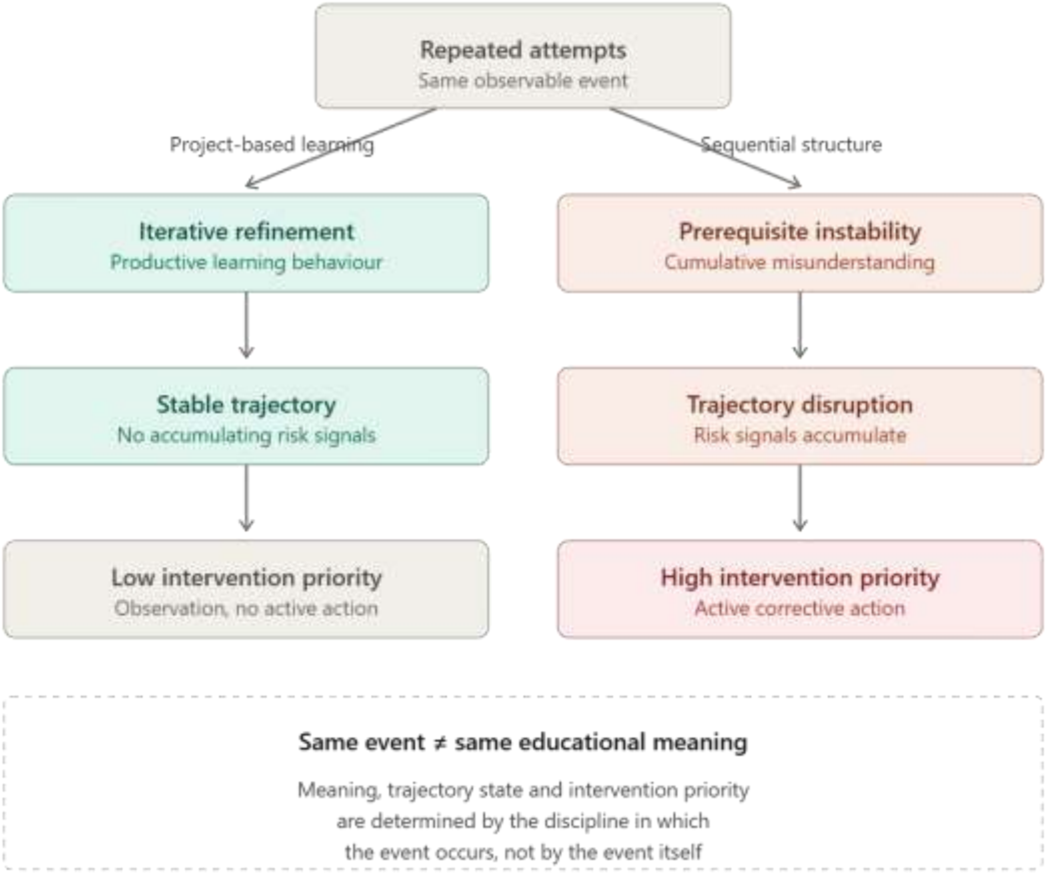

Figure 2. Context-Dependent Interpretation of the Same Event

This changes the role of adaptive systems in a substantive way. They stop being alert generators and start working as context-sensitive interpreters capable of reading the meaning of behaviour under conditions of uncertainty.

5. Discussion

The chief limitation of contemporary adaptive learning systems, on this analysis, is not a lack of data – it is the absence of stable mechanisms for reading those events in their setting.

Most existing learning analytics architectures remain event-centred in spirit. Events are treated as direct indicators of risk and intervention logic is built from relatively simple mappings between observable traces and adaptive actions, on the implicit assumption that behavioural indicators have stable meaning regardless of context.

The results of this study point the other way. Events are semantically underdetermined: their meaning shifts with the discipline, with the way the trajectory depends on prior topics, with temporal dynamics, with the learner's self-regulation, with the combinations in which events arise, and with where the learning activity is actually located. Under these conditions, single indicators are too unreliable to serve as direct triggers for action.

The limitation grows more pressing as digital educational environments become more heterogeneous. In hybrid, project-oriented and self-regulated settings, what one sees on the platform is only a partial projection of what is actually going on. Predictive systems that lean exclusively on LMS event streams find themselves on shakier and shakier interpretive ground.

The study also suggests that many problems traditionally framed as prediction problems are really interpretation problems in disguise. False positives often come not from any computational failure of the model, but from the simple fact that the events themselves do not carry stable meaning. The same event can mean productive engagement in one context and trajectory destabilisation in another. For the design of adaptive systems, this is a consequential distinction.

Much current research still channels effort into raising prediction accuracy – larger datasets, multimodal analytics, more elaborate machine-learning models, more sophisticated sequential prediction techniques. Our findings suggest that computational complexity alone will not resolve the underlying semantic ambiguity. Without machinery for reading events in context, even highly accurate models remain vulnerable to misreading learning behaviour.

The proposed architecture moves adaptive logic away from purely predictive event-processing and towards context-sensitive interpretive regulation. Within this framing, events are semantically incomplete; risk is treated as context-dependent; and intervention decisions emerge from interpretive reconstruction, not from event detection alone.

The approach also reshapes the role of teacher-facing analytics. Traditional dashboards routinely overload instructors with a mix of indicators that each demand interpretation. Under event-centred designs the teacher effectively becomes the system's implicit interpretive layer. Our model takes some of that interpretive load and shifts it into the architecture itself – instead of presenting bare deviations, the system assesses contextual stability before sending out an intervention signal. The expected payoffs are reduced cognitive load for teachers, lower intervention density, fewer false alerts and greater interpretive consistency across courses and disciplines.

The work also underlines the importance of trajectory-centred analysis. Instability rarely emerges from isolated events; it develops progressively through interacting configurations over time. Adaptive systems should therefore look not just at occurrence but at trajectory continuity, temporal accumulation, the patterns of event interaction and the stability of progression. Seen this way, adaptive learning systems look less like static predictive classifiers and more like dynamic regulation systems working under conditions of semantic uncertainty.

The architecture proposed here does not abolish uncertainty. Learning processes remain partially unobservable, contextually unstable, and shaped by factors that digital systems cannot see. What a context-sensitive interpretive layer does provide, however, is a noticeably more robust semantic foundation for adaptive intervention logic.

Several limitations should be acknowledged. First, the architecture is conceptual and interpretive rather than fully implemented in code – the focus here has been on architectural logic and semantic modelling rather than on algorithmic optimisation. Second, the analysis is restricted to two settings, namely project-based learning and marketing education; other disciplinary structures may well produce different interpretive dynamics. Third, the study focuses chiefly on event interpretation inside LMS-centred environments. Future work may extend the architecture into multimodal learning analytics, affective computing, the analysis of collaborative interaction and large-scale adaptive orchestration.

Despite these caveats, the findings indicate that future adaptive educational systems will increasingly need semantic, context-aware interpretive architectures and not purely event-driven predictive models.

6. Conclusion

The study lays out a fundamental semantic limitation in contemporary adaptive learning systems: observable events do not possess stable meaning outside of contextual interpretation.

Most learning analytics architectures still operate on event-centred logic in which behavioural deviations directly call forth adaptive responses. Our analysis shows that the same traces correspond to different learner states depending on disciplinary structure, trajectory dependency, self-regulation patterns, temporal dynamics, and the combinations in which events arise. On their own, single indicators cannot reliably serve as universal risk signals.

The context-sensitive interpretive architecture addresses this by inserting an interpretive layer between event detection and adaptive action. Within this framework, events are treated as semantically incomplete signals requiring contextual reconstruction before a decision to intervene is made. Educational instability, the study argues, does not arise from events themselves but from the way event configurations interact within the structure of a trajectory. Adaptive intervention should therefore be grounded in contextual interpretation of trajectory stability and not in direct event responsiveness.

The comparison between project-based learning and marketing education shows that repeated attempts, low LMS activity and missed deadlines acquire fundamentally different meanings under different contextual conditions. This challenges a key assumption of many contemporary predictive systems: that behaviour can be interpreted in a universal way.

The architecture also recasts adaptive systems: they move from generating predictive alerts towards exercising context-sensitive educational regulation, beginning to function as interpretive decision systems operating under semantic uncertainty. The growing importance of trajectory-centred analytics is another lesson that emerges: risk should be treated as a dynamic property arising from temporal accumulation, event interaction and contextual instability, and not as a static outcome of isolated behavioural deviations.

From a practical standpoint, the approach offers fewer false alarms, more stable interventions, lower cognitive load on instructors and a more semantically robust basis for adaptive logic. Further work might explore the computational implementation of this architecture, multimodal contextual interpretation, and the integration of semantic interpretive layers into large-scale adaptive learning platforms.

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