Data-Driven Instructional Management in Informatized Education: Threshold and Lag Effects of Online Learning Engagement

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Abstract

In informatized education, instructional management increasingly relies on behavioral data, yet conventional centralized approaches often overlook cohort heterogeneity and fail to capture the threshold and lag effects of online learning engagement. In this study, we propose an application-oriented analytical framework that integrates Distributed Lag Non-linear Modeling (DLNM) with Multivariate Meta-Analysis (MMA) under a summary-statistics-only integration strategy to support evidence-based instructional management without centralizing raw data. Within this framework, behavioral logs are retained at local instructional nodes, where DLNM is applied to estimate non-linear and time-lagged engagement–performance relationships; only node-level coefficients and covariance matrices are transmitted for global synthesis via MMA with Restricted Maximum Likelihood (REML), thereby establishing a technically explicit privacy boundary. We evaluate the proposed framework through two complementary stages: a controlled simulation first assesses parameter recovery under fragmented data conditions and benchmarks the framework against conventional pooling approaches, followed by a proof-of-concept empirical study using blended learning logs from 165 students across four instructional cohorts that examines the practical interpretability of the framework under real-world heterogeneity. The results reveal substantial between-cohort heterogeneity and a non-monotonic, inverted-U relationship between video engagement and academic performance. These findings demonstrate how established statistical methods can be systematically integrated into a governance-oriented analytical framework that enables threshold-aware, cohort-sensitive, and lag-aware instructional decision-making under privacy constraints.

CCS Concepts

• **General and reference → Reference works**.

Keywords

Informatized Education, Instructional Management, Online Learning Engagement, Lag Effects, DLNM-MMA

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1 Introduction

The rapid development of informatized education has transformed teaching and learning into increasingly data-rich processes, accelerating education toward a more connected and data-driven stage [23]. As online and blended learning environments continue to expand, traditional instructional boundaries of time and space are being reconfigured, giving rise to more flexible and self-organized learning modes [8]. This transformation has generated large volumes of behavioral log data, including interaction frequency, learning duration, and other process-oriented indicators. Effectively analyzing these high-dimensional behavioral data has therefore become an important issue in Educational Data Mining (EDM) and Learning Analytics (LA) to support instructional decision-making [3].

However, existing analytical approaches still face two major limitations. First, educational data are often distributed across platforms, classes, or institutions, and privacy regulations and data silo structures increasingly constrain centralized pooling. This makes it difficult to integrate raw data efficiently while preserving compliance, highlighting the need for distributed analytical approaches

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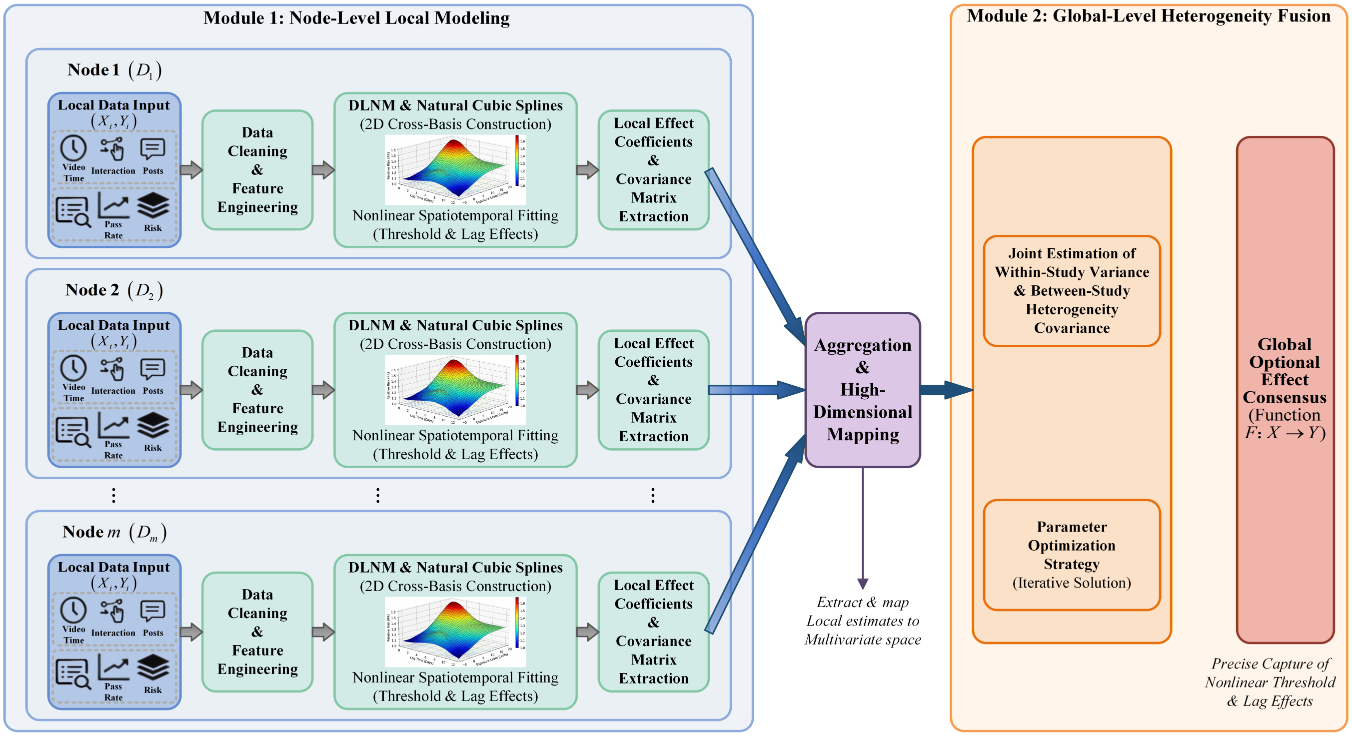

Figure 1: Framework overview of the proposed analytical framework under a summary-statistics-only integration strategy. At each local instructional node, raw behavioral logs remain in place and are analyzed with DLNM to estimate the threshold and lag effects of online learning engagement. Only node-level coefficients and covariance matrices are transmitted to the global MMA stage, where heterogeneous cohort-level evidence is synthesized without centralizing individual-level records.

that keep raw records localized [2]. Second, many conventional models rely on assumptions of linearity and homogeneity, which are often inconsistent with actual learning processes. In online learning contexts, engagement may not always produce proportional gains; instead, its marginal benefit may vary across intensity levels and may also unfold with temporal delay. Moreover, differences in instructional interventions and learner baselines may generate substantial heterogeneity across cohorts, which static global models tend to overlook [4].

Multivariate Meta-Analysis (MMA) provides a useful pathway for integrating heterogeneous and non-independent estimates across distributed data settings. Compared with univariate meta-analysis, MMA can jointly model correlated parameters through variance-covariance structures, thereby improving robustness in multidimensional estimation [14]. In parallel, the Distributed Lag Non-linear Model (DLNM) has been widely used to capture non-linear and lagged relationships in high-density time-series data. The combination of MMA and DLNM therefore offers a promising way to identify complex engagement–outcome patterns that conventional learning analytics models may fail to detect [9].

Accordingly, this study develops an application-oriented analytical framework for data-driven instructional management in informatized education under privacy constraints. The framework operates on two levels: at the local level, DLNM captures the non-linear and lagged effects of online learning engagement on academic performance within each cohort without sharing raw data; at the global level, MMA with Restricted Maximum Likelihood (REML) aggregates cohort-specific estimates while explicitly modeling between-cohort heterogeneity. The framework is evaluated through two complementary stages: a controlled simulation first assesses parameter recovery under fragmented data conditions and benchmarks the framework against conventional pooling approaches, followed by a proof-of-concept empirical study using real-world blended learning data that examines the practical interpretability of the framework under real-world heterogeneity.

This study makes three bounded contributions to data-driven instructional management in informatized education. First, it contributes an application-oriented integration of DLNM, MMA, and REML into a summary-statistics-only workflow for distributed educational data, rather than proposing a novel statistical estimator. Second, it shows that online learning engagement is threshold-sensitive, temporally lagged, and cohort-dependent in the present empirical setting. Third, it translates these regularities into decision-relevant implications for dosage regulation, follow-up evaluation windows, and cohort-specific intervention design under institutional data constraints.

2 Related Work

Research on online learning behavior has transitioned from descriptive learning analytics to predictive and intervention-focused modeling. Since learning analytics was formally framed as an emerging field [24], prior studies have developed theoretical perspectives and analytical tools for understanding online learning interactions [13], visualizing learning processes [6], and predicting learning trajectories or performance decline [1]. Common approaches in applied settings include predicting academic performance based on behavioral traces [16] and using social network methods for structural analysis of learning communities [15]. However, these studies are largely built on single-platform and centralized analytical settings, which makes them less suitable for current informatized education environments characterized by distributed data, cross-cohort variation, and dynamic behavioral processes. As a result, static models may obscure heterogeneity across instructional groups and oversimplify time-sensitive learning patterns [20].

To address heterogeneity in distributed educational data, meta-analysis offers an important foundation. Originating from effect-size aggregation across independent studies [11, 22], meta-analysis has been widely used to support evidence synthesis in multiple disciplines [26]. Yet classical univariate meta-analysis is not well suited to online learning data, where behavioral indicators are often correlated and temporally interdependent [5]. In this context, MMA provides a more appropriate solution by jointly estimating correlated effects through variance-covariance structures, thereby improving the integration of heterogeneous cohort-level evidence [28].

Another important gap in existing work concerns the dynamic relationship between learning engagement and learning outcomes. Prior educational studies rarely model both non-linear threshold effects and time-lagged effects simultaneously. In contrast, research in environmental epidemiology has shown that the DLNM is effective for identifying cumulative, non-linear, and delayed effects in dense time-series data [10]. This logic is relevant to online learning, where knowledge internalization is often delayed, and excessive continuous engagement may lead to cognitive overload, producing an inverted-U relationship between engagement and performance [25]. Therefore, integrating DLNM with MMA provides a suitable analytical pathway for modeling threshold, lag, and heterogeneity effects in data-driven instructional management.

3 Methods

To support data-driven instructional management in informatized education, this study develops a distributed analytical framework under privacy constraints for identifying the threshold and lag effects of online learning engagement. The framework is designed for instructional settings in which behavioral data are stored across multiple educational nodes and cannot be directly pooled. It combines DLNM for local estimation with MMA for global integration, while Restricted Maximum Likelihood (REML) is used to obtain more robust estimates of cross-cohort heterogeneity.

3.1 Analytical Overview

In online and blended learning environments, behavioral data are often distributed across classes, platforms, or campuses. Let the complete dataset be denoted as $D = \{D_1, D_2, \ldots, D_m\}$, where the local dataset at node i is $D_i = \{X_{i,t}, Y_{i,t}\}$. Here, $X_{i,t}$ denotes learning engagement variables measured over time, such as video viewing duration and interaction frequency, and $Y_{i,t}$ denotes the corresponding learning outcome at time step t.

The objective is to estimate the engagement-performance relationship without sharing raw data across nodes. To achieve this, we adopt a two-stage analytical pipeline (Fig 1). In the first stage, DLNM is fitted locally to model non-linear and lagged engagement-outcome relationships and to extract node-specific coefficients together with their covariance matrices. In the second stage, MMA integrates these local estimates to identify a global pattern while explicitly accounting for heterogeneity across instructional cohorts. This design supports distributed evidence integration for instructional management under privacy constraints.

The privacy-related contribution of the framework lies in architectural data minimization rather than formal privacy guarantees. Raw clickstream logs and learner-level outcome records remain at local instructional nodes, and the central synthesis layer receives only cohort-level coefficients and covariance matrices. Accordingly, the proposed design should be interpreted as a summary-statistics-only integration strategy that reduces raw-data circulation under institutional privacy constraints, rather than as an implementation of differential privacy, secure multi-party computation, or cryptographic federated aggregation [7?].

3.2 Local Modeling with DLNM

The local modeling stage is grounded in Cognitive Load Theory [18]. In online learning, engagement does not necessarily produce proportional gains: moderate engagement may improve performance, whereas excessive continuous engagement may lead to working-memory overload and diminishing returns. At the same time, the effect of engagement may not be immediate, because knowledge internalization often unfolds over a temporal delay. To capture these two features, we employ the DLNM at each node [10]. As shown in Fig 2, the DLNM models local engagement–outcome relationships by jointly representing exposure intensity and lag structure in a bi-dimensional cross-basis space.

DLNM constructs a bi-dimensional cross-basis over the exposure dimension and the lag dimension, allowing the model to represent both threshold effects and lag effects in time-series engagement data. For binary outcomes, the local probabilistic model can be written as

$$P(y = 1 \mid X) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4)}. \quad (1)$$

In Eq. (1), $y \in \{0, 1\}$ denotes the learning outcome, $X = [x_1, \ldots, x_4]$ denotes the extracted engagement features, $\beta = [\beta_1, \ldots, \beta_4]^\top$ denotes the coefficient vector after cross-basis transformation, and β_0 is the intercept. For continuous outcomes such as final grades, the local model can be implemented within a generalized linear modeling framework using link and variance structures chosen to match the empirical characteristics of the observed outcome distribution.

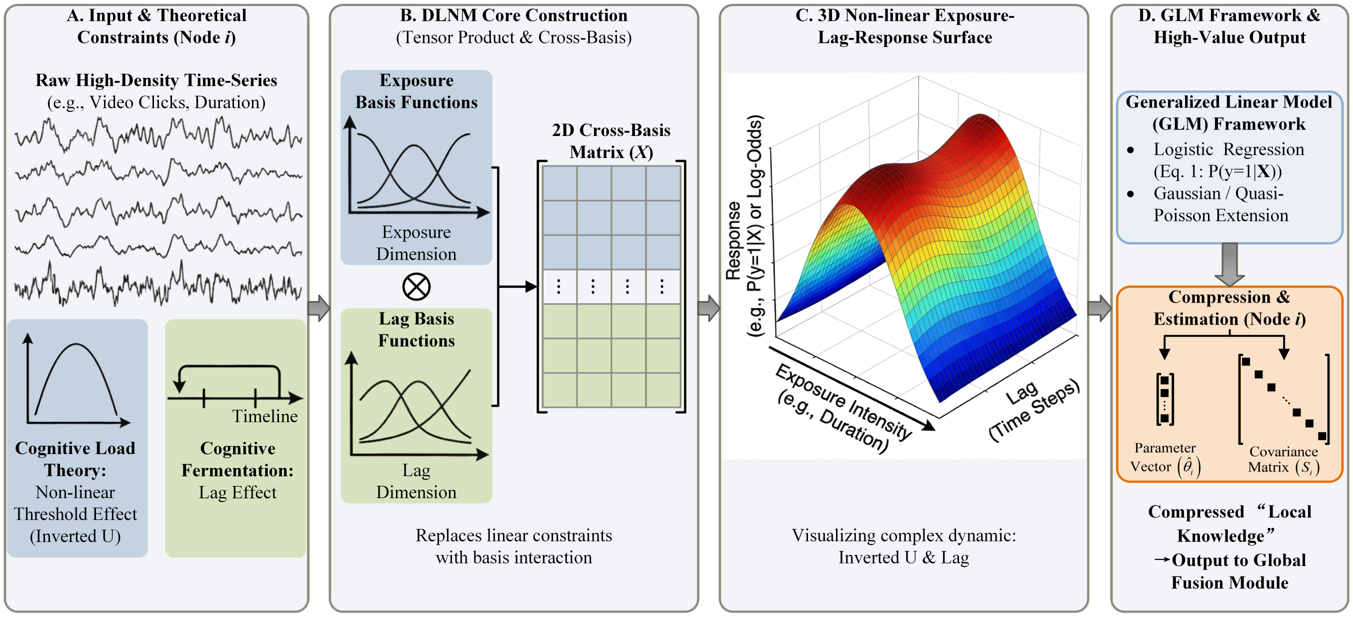

Figure 2: Architectural diagram of the local DLNM modeling stage in the proposed analytical pipeline. For each instructional node, a bi-dimensional cross-basis is constructed from learning engagement duration and lag time to capture the threshold and lag effects of online learning engagement. The fitted DLNM generates a non-linear exposure–response surface and produces node-specific coefficients and covariance matrices, which are passed to the global MMA stage for evidence integration under privacy constraints.

After local fitting, each node produces a parameter estimate vector $\hat{\theta}_i$ and its covariance matrix S_i. These quantities summarize the local engagement-performance relationship and serve as inputs to the global integration stage.

3.3 Global Integration with MMA

Because instructional cohorts may differ in learner baseline, teaching intervention, and contextual conditions, local estimates are expected to be heterogeneous. To integrate these non-independent local results, we apply MMA [14].

Let y_i denote the vector of local effect estimates for node i. Under the random-effects formulation, the marginal model is

$$y_i \sim MVN(\mu,\ S_i + \Delta), \tag{2}$$

where μ is the global mean effect vector, S_i is the within-node covariance matrix estimated from the DLNM, and Δ is the between-node heterogeneity covariance matrix.

To further account for contextual differences across instructional units, the model can be extended to a multivariate meta-regression:

$$y_i = X_i\beta + \delta_i + e_i, \tag{3}$$

where X_i is the design matrix of cohort-level covariates, β is the fixed-effect vector, $\delta_i \sim MVN(0, \Delta)$ represents between-node random effects, and $e_i \sim MVN(0, S_i)$ denotes within-node residual variation.

This formulation enables the framework to synthesize heterogeneous cohort-level evidence while preserving the local variance structure of each instructional unit.

3.4 REML Estimation

A key challenge in Eqs. (2) and (3) is the estimation of the heterogeneity matrix Δ. Standard maximum likelihood estimation may underestimate variance components in finite samples. To reduce this bias, we adopt Restricted Maximum Likelihood (REML) [19].

Under generalized least squares, the fixed-effect estimator is

$$\hat{\beta} = \left(\sum_{i=1}^{m} X_i^{\top}(S_i + \Delta)^{-1} X_i\right)^{-1} \left(\sum_{i=1}^{m} X_i^{\top}(S_i + \Delta)^{-1} y_i\right). \tag{4}$$

REML estimates Δ in a transformed space that is orthogonal to the fixed effects. Let A be a transformation matrix satisfying $AX = 0$. The transformed model is

$$Ay = A\delta + Ae. \tag{5}$$

Based on this transformation, the REML objective can be written as

$$l_{\text{REML}}(\Delta) = l_{\text{MLE}}(\Delta) - \frac{1}{2}\log\left|\sum_{i=1}^{m} X_i^{\top}(S_i + \Delta)^{-1} X_i\right|. \tag{6}$$

The estimation proceeds iteratively: β is updated using generalized least squares, and Δ is then re-estimated in the orthogonal subspace until convergence. Compared with conventional maximum likelihood estimation, this strategy provides more stable heterogeneity estimates for distributed educational data characterized by dependence, multicollinearity, and cross-cohort variation.

Overall, the proposed framework provides a concise analytical strategy for identifying threshold effects, lag effects, and cohort heterogeneity in online learning engagement, while supporting evidence integration under privacy constraints for instructional management in informatized education.

4 Experiments and Analysis

This section evaluates how useful the proposed framework is for supporting data-driven instructional management in distributed and heterogeneous educational settings. The empirical evaluation proceeds through two complementary stages. In the first stage, a controlled simulation is conducted to assess parameter recovery under fragmented data conditions and to benchmark the proposed framework against conventional pooling approaches. In the second stage, a proof-of-concept empirical study is conducted to examine whether the framework can reliably identify threshold effects, temporal lag structures, and between-cohort heterogeneity in real-world blended learning data. The simulation is specifically designed to evaluate the statistical robustness of distributed summary-statistics aggregation under controlled fragmentation conditions, with its scope bounded to internal statistical validation rather than extending to the full institutional complexity characteristic of authentic educational environments.

4.1 Experimental Design

The analytical pipeline was implemented using Python 3.8 and R. Python (Torch 2.4.0, CUDA 12.1) was used for Monte Carlo simulation and data preprocessing, while the `dlnm` (v2.4.7) and `mvmeta` (v1.1.3) packages in R were used for DLNM and MMA estimation. To reduce space, hardware details are omitted here because they do not affect the substantive interpretation of the results.

Two datasets were used. First, for simulation, we generated 100,000 samples from a multidimensional logistic model with four exposure variables and a true parameter vector $\beta = [0, 1, 1.2, 2, 2.5]^{\top}$. The generated data were randomly partitioned into 20 and 100 independent blocks to simulate distributed educational nodes under different levels of fragmentation. Second, for empirical evaluation, we used anonymized behavioral logs from a blended university course, *Database Principles and Applications*. The dataset contains 165 learners from four instructional cohorts (`data2002`, `jike2001`, `ds2001`, and `jike1901`). Two engagement indicators were analyzed: chapter access frequency and video viewing duration. Final comprehensive score was used as the outcome variable.

To evaluate simulation performance, we used the Mahalanobis distance

$$D_M = (\hat{\beta} - \beta)^{\top} \Sigma^{-1} (\hat{\beta} - \beta), \tag{7}$$

where Σ denotes the covariance matrix of the estimated parameters. Smaller D_M and lower total standard deviation indicate more accurate recovery of the true parameter vector.

For the empirical analysis, local estimation used an outcome-appropriate generalized linear specification with variance adjustment to address cohort-level clustering and potential dispersion in the observed instructional data. Cross-cohort heterogeneity was evaluated using Cochran's Q and the I^2 statistic:

$$I^2 = \max\left(0, \frac{Q - (k-1)}{Q}\right) \times 100\%, \tag{8}$$

where k is the number of instructional nodes. Consistent with conventional practice, substantial heterogeneity is indicated when $I^2 > 50\%$ or $p < 0.05$ [12].

For local DLNM estimation, natural cubic splines were used for both exposure and lag dimensions, with internal knots placed at the 10th, 50th, and 90th percentiles. The maximum lag window was set to 21 days with log-spaced lag knots. In the global integration stage, REML was used to estimate the heterogeneity matrix, and the convergence threshold was set to 1.0×10^{-6}.

4.2 Results

4.2.1 Simulation Results. Table 1 compares the proposed MMA-based aggregation with simple averaging under two fragmentation settings. Across both conditions, MMA consistently produced smaller Mahalanobis distances and substantially lower total standard deviations, indicating more stable recovery of the true parameter vector.

The results suggest that MMA provides more robust parameter integration than naive pooling in distributed learning data. However, performance deteriorates as fragmentation becomes more extreme: when the number of blocks increases from 20 to 100, the Mahalanobis distance rises under both strategies. This finding indicates that under privacy constraints distributed analysis also involves a practical trade-off: excessive fragmentation may reduce local sample support and weaken estimation precision. For instructional analytics, this implies that distributed evidence integration should balance privacy constraints with sufficient cohort-level data quality.

4.2.2 Empirical Results. We next applied the framework to the real blended learning dataset. Local estimation was conducted within the generalized linear specification described above to account for clustering and overdispersion inherent in instructional count and duration data. Table 2 summarizes the descriptive characteristics and cohort-level heterogeneity statistics for both engagement indicators.

Chapter access frequency. The cross-basis coefficients for chapter access frequency were statistically significant at the cohort level ($Q = 98.72$, $df = 36$, $p < 0.001$), and the proportion of total variance attributable to between-cohort heterogeneity was substantial ($I^2 = 63.5\%$). This magnitude of heterogeneity indicates that the engagement–performance relationship is not stable across instructional contexts: cohorts differ markedly in the degree to which chapter access translates into measurable learning gains. Such variation is plausibly attributable to differences in pedagogical design, baseline learner preparation, and class-level interaction norms that mediate the conversion of reading behavior into academic output. From a methodological standpoint, this result directly motivates the distributed integration strategy adopted in the present framework. A naive pooled estimator would conflate structurally distinct cohort effects, producing a composite that misrepresents the true engagement dynamics within any individual cohort and affords a limited basis for cohort-sensitive instructional governance.

Video viewing duration. For video viewing duration, cohort-level effects were similarly significant ($Q = 103.27$, $df = 45$, $p < 0.001$;

Table 1: Simulation Results under Different Data Partition Settings

Partition	D_M (MMA)	D_M (Simple Avg.)	Total SD (MMA)	Total SD (Simple Avg.)
20 blocks	1.9842	2.1608	1.06E-01	4.31E-01
100 blocks	2.7026	3.0493	1.00E-01	9.80E-01

Table 2: Empirical Summary of Engagement Indicators and Heterogeneity

Indicator	Descriptive statistics	Heterogeneity statistics
Chapter access frequency	$N = 165$, Min = 73, Max = 477, Mean = 203, SD = 60	$Q = 98.7166$, $df = 36$, $p < 0.001$, $I^2 = 63.5\%$
Video viewing duration	$N = 165$, Min = 48.1, Max = 1027.8, Mean = 595.5, SD = 159.5	$Q = 103.2740$, $df = 45$, $p < 0.001$, $I^2 = 56.4\%$

$I^2 = 56.4\%$), confirming that the engagement–performance association for video-based activities is likewise heterogeneous across instructional groups. Beyond the heterogeneity diagnostic, the aggregated exposure–response curve presented in Fig. 3 reveals a structurally important non-linearity: academic performance increases with cumulative video engagement over the initial range of exposure but declines beyond an intermediate threshold, yielding an inverted-U profile. This pattern is theoretically coherent with cognitive load theory [25], which posits that working memory capacity is finite and that sustained high-intensity processing eventually impairs rather than facilitates learning. The empirical result, therefore, cautions against treating cumulative viewing time as a monotonically beneficial indicator; sustained exposure beyond a critical threshold may be associated with attentional fatigue, reduced elaborative processing, or disengagement from active learning strategies.

For instructional management, the combined curve also supports a practical interpretation in three zones. Operationally, this tri-zone interpretation supports three immediate management actions: reinforcing participation in under-engagement cohorts, maintaining learners within the effective-dosage range through shorter and segmented video design, and triggering review prompts or temporary interruption mechanisms when cohort-specific exposure trajectories approach the overload-risk region. The low-exposure region can be read as an under-engagement zone, in which additional guided participation is likely to be beneficial. The middle range represents an effective dosage zone, in which engagement is associated with the strongest positive learning returns. The high-exposure tail represents a possible overload-risk zone, where longer periods of continuous viewing result in diminishing or even negative returns. This interpretation suggests that managers should favor shorter video segments, threshold-triggered reminders, and distributed learning schedules rather than treating longer viewing time as an unconditional indicator of better learning. Because the empirical sample does not support stable estimation of a universal cutoff applicable to all contexts, the present study interprets the threshold qualitatively rather than prescribing a single fixed benchmark.

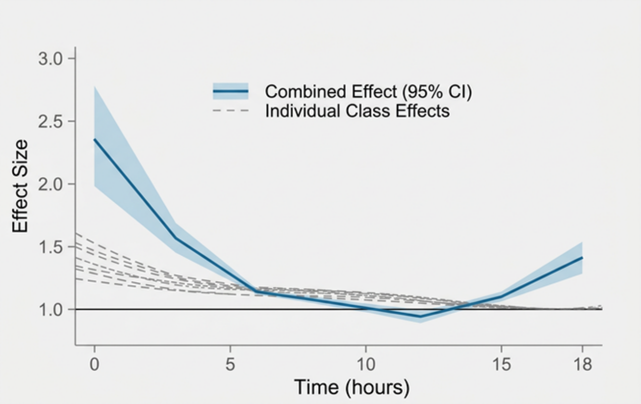

Figure 3: Estimated engagement–performance relationship for video viewing duration in the proposed analytical pipeline. The solid curve with a shaded confidence band represents the globally combined effect obtained by aggregating cohort-level cross-basis estimates; dashed curves correspond to cohort-specific local estimates. The combined curve exhibits a non-linear inverted-U profile, indicating a threshold effect whereby performance gains associated with increased video engagement diminish and ultimately reverse beyond an intermediate exposure level. Cross-cohort variation in the local curves further illustrates the heterogeneity that motivates cohort-sensitive analysis.

Taken together, the empirical results support a bounded conclusion. First, online learning engagement is heterogeneous across instructional cohorts, which justifies distributed evidence integration rather than direct pooling. Second, the relationship between engagement and performance is dynamic rather than linear, especially for video-based learning behaviors. Third, these findings can be translated into an actionable management logic: instructional governance should distinguish insufficient engagement, effective engagement, and overload-risk rather than maximize exposure indiscriminately.

4.3 Limitations

This study has three main limitations. First, the current framework relies primarily on explicit behavioral logs, such as access frequency and viewing duration. Although these indicators are useful proxies for engagement, they do not directly capture deeper cognitive and affective processes. Future research may incorporate multimodal signals, such as eye-tracking, physiological data, or semantic features extracted from discussion texts, to improve the representation of learning processes [17].

Second, the proposed framework aims to identify strong nonlinear and lagged relationships, but it does not define definitive causal effects. Learning performance is shaped by multiple interacting factors, including prior knowledge, motivation, and instructional support. Therefore, future work could integrate causal inference tools, such as directed acyclic graphs or causal representation learning, to strengthen the interpretability of intervention recommendations [27].

Third, the empirical evidence is drawn from a single blended university course with four instructional cohorts. This design adequately illustrates threshold, lag, and heterogeneity patterns; however, its generalizability to other educational environments, institutions, or vocational training contexts requires additional validation.

5 Discussion

This study challenges the conventional assumption that online learning engagement linearly predicts academic performance, advancing data-driven pedagogical governance in technology-enhanced learning. The empirical findings reveal a significant inverted U-shaped association between video viewing duration and academic outcomes. Sustained engagement yields positive returns only within a specific threshold range; beyond this critical point, excessive exposure induces cognitive overload and diminishes learning efficiency, consistent with Cognitive Load Theory [25]. The substantial heterogeneity observed across teaching cohorts indicates that engagement patterns are jointly shaped by baseline academic preparedness, instructional intervention intensity, and classroom dynamics rather than individual behaviors alone.

These findings establish threshold, lag, and heterogeneity as foundational prerequisites for informed governance in technology-enhanced instruction, not merely technical data characteristics. The inverted U-shaped effect supports a “tri-zone interpretive framework” delineating learning behaviors into under-engagement, effective dosage, and overload risk zones. This necessitates a paradigm shift from descriptive monitoring of “maximizing learner activity” toward decision-oriented governance of “maintaining engagement within the effective zone.” The framework's core contribution lies in exposing the limitations of immediate outcome evaluation. Given the temporal delay in translating engagement into performance gains, instructional administrators must allocate adequate follow-up observation windows when assessing knowledge consolidation interventions, avoiding premature dismissal due to absent short-term effects.

Methodologically, this study demonstrates the necessity and feasibility of distributed pedagogical analytics under privacy-preserving constraints. The heterogeneity indices—$I^2 = 63.5\%$ for chapter access frequency and $I^2 = 56.4\%$ for video viewing duration—reveal a critical concern: centralized data pooling risks obscuring genuine population heterogeneity. Under such pronounced heterogeneity, global static models fail to capture local regularities and may precipitate Simpson's paradox [21]. The DLNM-MMA framework preserves local variance structures while protecting raw data privacy. Simulation experiments corroborate that this distributed evidence synthesis approach yields reduced Mahalanobis distances and lower estimation variance, establishing a robust pathway for cross-cohort pedagogical analysis.

Practically, these results call for “threshold-aware” and “cohort-sensitive” precision intervention mechanisms. Platform-level monitoring should move beyond activity counts toward dynamic identification of whether sustained engagement approaches the critical inflection point where efficiency reverses. The observed patterns reveal that concentrated last-minute engagement fails to facilitate sustained knowledge internalization; instructional designers should decompose macro-level objectives into distributed micro-learning units, steering behaviors from “post-hoc outcome tracking” toward “process-oriented rhythmic regulation.” Given inherent cohort differences, standardized protocols demonstrate limited effectiveness; intervention timing and intensity require adaptive calibration according to local instructional conditions.

While the empirical evidence derives from hybrid university courses, the governance principles possess significant extensibility to e-commerce education and digital vocational training. In e-commerce education settings—such as live-streaming commerce, digital marketing, and platform operation training—learning processes are characterized by significant task orientation, platform dependency, and performance sensitivity. High-frequency repetitive learning and rapid skill conversion render threshold effects, return lags, and prior experience heterogeneity particularly consequential for managerial decision-making. Excessive continuous instruction may attenuate training transfer rates, while learner background variation necessitates differentiated pacing. This study furnishes analytical tools for hybrid learning behavior analysis and provides a generalizable pedagogical governance template for e-commerce settings requiring cross-cohort evidence integration without centralizing raw data. Nevertheless, the current empirical component constitutes a proof-of-concept demonstration; generalizability of these pedagogical governance implications awaits validation across larger-scale, more diversified educational and vocational training environments.

6 Conclusion

This study proposes a distributed analytical framework integrating Distributed Lag Non-linear Modeling (DLNM) with Multivariate Meta-Analysis (MMA) for data-driven instructional management under privacy constraints. Through Monte Carlo simulation and empirical analysis of blended learning logs from 165 students across four instructional cohorts, the framework demonstrates effectiveness in modeling nonlinear, lagged, and heterogeneous engagement-performance relationships without centralizing raw data. The results provide three significant contributions: first, online learning engagement demonstrates threshold effects and temporal dynamics instead of straightforward monotonic returns; second, considerable cohort heterogeneity represents a critical analytical factor rather than a mere statistical inconvenience; and third, privacy-preserving evidence integration facilitates comprehensive instructional analysis when data pooling is not possible. This study repositions instructional analytics from outcome prediction toward the identification of governance-relevant regularities, generating actionable evidence for threshold-aware, cohort-sensitive, and privacy-conscious pedagogical intervention in technology-enhanced learning environments.

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References

[1] Bayan Alnasyan, Mohammed Basheri, and Madini Alassafi. 2024. The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review. *Computers and Education: Artificial Intelligence* 6 (2024), 100231.

[2] Daniel Amo-Filva, David Fonseca, Francisco José García-Peñalvo, Marc Alier Forment, Maria José Casany Guerrero, and Guillem Godoy. 2024. Exploring the landscape of learning analytics privacy in fog and edge computing: A systematic literature review. *Computers in human behavior* 158 (2024), 108303.

[3] Ryan S. Baker and George Siemens. 2022. Learning Analytics and Educational Data Mining. In *The Cambridge Handbook of the Learning Sciences*, R. Keith Sawyer (Ed.). Cambridge University Press, 259–278. doi:10.1017/9781108888295.016

[4] Nina Bergdahl, Melissa Bond, Jeanette Sjöberg, Mark Dougherty, and Emily Oxley. 2024. Unpacking student engagement in higher education learning analytics: a systematic review. *International Journal of Educational Technology in Higher Education* 21, 1 (2024), 63.

[5] Danielle L. Burke, Thomas A. Trikalinos, Christopher H. Schmid, Yong Chen, Dan Jackson, and Richard D. Riley. 2022. Multivariate Meta-Analysis of Multiple Outcomes: Characteristics and Predictors of Borrowing of Strength from Cochrane Reviews. *Systematic Reviews* 11, 1, Article 149 (2022). doi:10.1186/s13643-022-01999-0

[6] Luís Cabral, Rui Pinto, and Gil Gonçalves. 2025. AI-powered learning analytics dashboards: a systematic review of applications, techniques, and research gaps. *Discover Education* 4, 1 (2025), 525.

[7] Cynthia Dwork and Aaron Roth. 2014. *The Algorithmic Foundations of Differential Privacy*. Vol. 9. Now Publishers, Hanover, MA. 211–407 pages. doi:10.1561/0400000042

[8] Ahmad Faza and Ilyana Agri Lestari. 2025. Self-regulated learning in the digital age: A systematic review of strategies, technologies, benefits, and challenges. *International Review of Research in Open and Distributed Learning* 26, 2 (2025), 23–58.

[9] Antonio Gasparrini and Ben Armstrong. 2013. Reducing and Meta-Analysing Estimates from Distributed Lag Non-Linear Models. *BMC Medical Research Methodology* 13, 1, Article 1 (2013). doi:10.1186/1471-2288-13-1

[10] Antonio Gasparrini, Ben Armstrong, and Michael G. Kenward. 2010. Distributed Lag Non-Linear Models. *Statistics in Medicine* 29, 21 (2010), 2224–2234. doi:10.1002/sim.3940

[11] Gene V. Glass. 1976. Primary, Secondary, and Meta-Analysis of Research. *Educational Researcher* 5, 10 (1976), 3–8.

[12] Julian P. T. Higgins, Simon G. Thompson, Jonathan J. Deeks, and Douglas G. Altman. 2003. Measuring Inconsistency in Meta-Analyses. *BMJ* 327, 7414 (2003), 557–560. doi:10.1136/bmj.327.7414.557

[13] Juan Hu and Wen Xiao. 2025. What are the influencing factors of online learning engagement? A systematic literature review. *Frontiers in Psychology* 16 (2025), 1542652.

[14] Dan Jackson, Richard D. Riley, and Ian R. White. 2011. Multivariate Meta-Analysis: Potential and Promise. *Statistics in Medicine* 30, 20 (2011), 2481–2498. doi:10.1002/sim.4172

[15] Rogers Kaliisa, Bart Rienties, Anders I Mørch, and Anders Kluge. 2022. Social learning analytics in computer-supported collaborative learning environments: A systematic review of empirical studies. *Computers and Education Open* 3 (2022), 100073.

[16] Yutong Liu, Si Fan, Shuxiang Xu, Atul Sajjanhar, Soonja Yeom, and Yuchen Wei. 2022. Predicting student performance using clickstream data and machine learning. *Education Sciences* 13, 1 (2022), 17.

[17] Fan Ouyang and Xianping Bai. 2026. A systematic review of multimodal learning analytics in computer-supported collaborative learning. *Computers & Education* (2026), 105574.

[18] Fred Paas, Alexander Renkl, and John Sweller. 2003. Cognitive Load Theory and Instructional Design: Recent Developments. *Educational Psychologist* 38, 1 (2003), 1–4. doi:10.1207/S15326985EP3801_1

[19] H. D. Patterson and Robin Thompson. 1971. Recovery of Inter-Block Information When Block Sizes Are Unequal. *Biometrika* 58, 3 (1971), 545–554. doi:10.1093/biomet/58.3.545

[20] Robert L. Peach, Sam F. Greenbury, Iain G. Johnston, Sophia N. Yaliraki, David J. Lefevre, and Mauricio Barahona. 2021. Understanding Learner Behaviour in Online Courses with Bayesian Modelling and Time Series Characterisation. *Scientific Reports* 11, 1, Article 2823 (2021). doi:10.1038/s41598-021-81709-3

[21] Judea Pearl. 2014. Comment: Understanding Simpson's Paradox. *The American Statistician* 68, 1 (2014), 8–13. doi:10.1080/00031305.2014.876829

[22] Karl Pearson. 1904. Report on Certain Enteric Fever Inoculation Statistics. *BMJ* 2, 2288 (1904), 1243–1246. doi:10.1136/bmj.2.2288.1243

[23] Jenay Robert, Nicole Muscanell, Mark McCormack, Kathe Pelletier, Kim Arnold, Nichole Arbino, Keturah Young, and Jamie Reeves. 2025. 2025 EDUCAUSE Horizon Report: teaching and learning edition. *Horizon Report* (2025).

[24] George Siemens and Phil Long. 2011. Penetrating the Fog: Analytics in Learning and Education. *EDUCAUSE Review* 46, 5 (2011), 30–40. https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education

[25] John Sweller. 1988. Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science* 12, 2 (1988), 257–285. doi:10.1016/0364-0213(88)90023-7

[26] Eric Trahan. 1993. Applying Meta-Analysis to Library and Information Science Research. *The Library Quarterly* 63, 1 (1993), 73–91.

[27] Joshua Weidlich, Dragan Gašević, and Hendrik Drachsler. 2022. Causal inference and bias in learning analytics: A primer on pitfalls using directed acyclic graphs. *Journal of Learning Analytics* 9, 3 (2022), 183–199.

[28] Ian R. Weir, Lu Tian, and Ludovic Trinquart. 2021. Multivariate Meta-Analysis Model for the Difference in Restricted Mean Survival Times. *Biostatistics* 22, 1 (2021), 82–96. doi:10.1093/biostatistics/kxz018

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