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Tailoring the Digital Campus: Design and Semester-Long Field Evaluation of an Adaptive User Interface in Moodle LMS

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Abstract—Most university learning platforms continue to serve identical, rigid menus and resource listings to all students regardless of how quickly they learn or what study habits they show. This uniform setup often creates needless friction, causing students to lose time searching for materials instead of focusing on their coursework. In this study, we built and tested an Intelligent User Interface (IUI) that plugs directly into an active university Moodle environment without changing core system files. The platform pairs a recommendation pipeline—blending collaborative filtering via Singular Value Decomposition with text-based content similarity—with an adaptive dashboard and responsive drawer navigation. Over a 16-week term, we tracked 520 university students and gathered both continuous background clickstream logs and mid-term survey feedback on usability (SUS), satisfaction (ACSI), and engagement (UWES-S). Using partial least squares structural equation modeling (PLS-SEM) and 5,000 bootstrap resamples, we evaluated how the interface influenced study habits and final grades. Recommendation tests showed strong ranking accuracy (Precision@5 = 0.842, NDCG@5 = 0.865) while adding only 41.8 ms in server processing time. Structural models indicated that interface interaction directly improved student engagement ($\beta = 0.438$, $p < 0.001$) and final marks ($\beta = 0.285$, $p < 0.001$), explaining 44.8% of variance in engagement and 35.6% of final course marks. Mediation analysis revealed that student engagement served as a substantial partial bridge (indirect effect $\beta = 0.142$, accounting for 33.25% of total effect). These findings show that universities can meaningfully upgrade existing Moodle setups with lightweight adaptive plugins that ease navigation, keep students involved, and improve academic performance.

Keywords: Intelligent User Interfaces, Personalized Learning, Moodle, Learning Analytics, Systematic Literature Review, Recommendation Systems, Student Engagement, Academic Achievement, Higher Education.

1. Introduction

Over the last two decades, learning management systems (LMSs) like Moodle and Canvas have become the default operating systems of higher education [5], [11]. They handle everything from distributing lecture recordings and hosting discussion boards to processing weekly assignments and managing gradebooks [1], [5]. In running these everyday tasks, university LMS servers record vast trails of student activity—when learners log in, how long they view readings, which practice questions trip them up, and how they move through course modules [10], [14].

Yet, despite all this rich tracking data, standard university course portals remain remarkably stubborn in their layout [7]. Whether a student enters a course with strong foundational knowledge, struggles with basic concepts, logs in every evening, or rushes through assignments at the last minute, the LMS presents the exact same nested folder trees and static lists of PDFs [3], [7]. Everyone gets the same view [4], [9].

This one-size-fits-all structure creates unnecessary friction [4], [19]. In cognitive ergonomics, this friction is known as extraneous cognitive load: mental effort spent figuring out where a file is saved or remembering which prerequisite was missed, rather than actually understanding the subject matter [4], [9]. When students spend several minutes digging through multi-level folder directories, their attention splinters [11], [13]. For students already struggling to stay motivated, this extra effort often leads to passive browsing, missed deadlines, and creeping disengagement [13], [14].

Personalized online learning seeks to fix this mismatch by adapting content, pacing, and visual prompts to how an individual actually studies [1], [2]. Historically, giving students tailored pathways required either custom intelligent tutoring platforms that sat outside standard university infrastructure or heavy manual grading and feedback from teaching staff [3], [18]. Intelligent User Interfaces (IUIs) offer a more practical path forward [8], [11]. By bringing adaptive logic right into the presentation layer of the institutional LMS, an IUI turns a static file directory into a responsive study assistant [3], [8].

Rather than forcing students to conform to a single layout, an adaptive interface reads real-time clickstream patterns and dynamically adjusts what it shows [8], [18]. It can surface a 'Next Best Step' reading carousel, adjust side navigation drawers to highlight upcoming tasks, and provide gentle visual nudges when study cadence drops off [3], [8].

While educational data mining and learning analytics have expanded rapidly, three practical challenges remain common in the literature:

1. Disconnection from Live Enterprise LMSs: Many adaptive learning prototypes are tested in artificial computer labs or custom-built standalone software rather than inside the production LMS platforms that universities rely on day-to-day [7], [11].
2. Missing Implementation and Latency Details: Research papers frequently treat recommendation engines as abstract conceptual diagrams, offering little data on algorithmic blending, cold-start handling, or server response times under real classroom loads [10], [18].
3. Basic Statistical Analysis: Many evaluations stop at simple correlations or ordinary regression models without validating latent survey constructs through structural equation modeling (SEM) or testing whether engagement truly mediates student success [13], [21], [22].

To address these gaps, this paper describes the design, deployment, and semester-long evaluation of an Intelligent User Interface embedded directly in an operational Moodle LMS at a university campus. Our work makes four specific contributions:

- We present a decoupled five-tier system architecture that ties Moodle Event Observers and REST APIs to a standalone Python adaptive microservice, preserving core LMS stability while adding less than 45 ms in server response latency.
- We formulate a hybrid recommendation model that combines Matrix Factorization (SVD) with text-based TF-IDF similarity, using a logistic threshold to smoothly guide new students before they build extensive history on the platform.
- We combine objective clickstream telemetry (active study days, reading views, quiz submissions, module completion) with established psychometric scales (SUS, ACSI, UWES-S) collected across 520 students over a full 16-week term.
- We validate the complete structural path model using PLS-SEM and 5,000 bootstrap resamples, demonstrating both direct gains and an indirect engagement pathway linking interface interactions to final course performance.

2. Systematic Literature Review and Theoretical Framework

To anchor our study within the broader academic discourse, we synthesized literature across five related areas: LMS navigation constraints, adaptive interfaces in HCI, learning analytics recommender engines, technology acceptance models, and student engagement theory. Table 1 summarizes the core foundations, recent findings, and practical gaps that this study bridges.

Research Domain	Key Studies & Authors	Core Theoretical Findings	Gaps Addressed in This Study
LMS Ergonomics & Constraints	Coates et al. [5]; Alario-Hoyos et al. [7]; Vasu et al. [11]	Standardized LMS layouts create cognitive friction, causing navigational fatigue and failing to support varied self-study rhythms.	Deploys non-intrusive adaptive UI blocks directly on an institutional Moodle installation.
Adaptive UI & Scaffolding in HCI	Horvitz [8]; Jameson [3]; Norman [4]; Brusilovsky [18]	Interfaces that anticipate user intent close the Gulfs of Execution and Evaluation, freeing mental energy for core learning tasks.	Validates mixed-initiative adaptive interfaces in a live course setting rather than a lab prototype.
Learning Analytics & Recommenders	Siemens & Gasevic [1]; Khor & Wong [10]; Baker & Corbett [26]	Combining collaborative and content filtering yields accurate resource suggestions while resolving student cold-start issues.	Provides complete algorithmic formulas, Top-K precision curves, and real-time latency breakdowns.
Technology Acceptance & Usability	Davis [15]; Brooke [19]; Fornell & Larcker [29]	Perceived ease of use directly drives learner satisfaction and ongoing adoption of digital learning tools.	Uses standardized SUS and ACSI instruments to ensure solid reliability and discriminant validity.

Engagement Theory & Mediation	Kuh [12]; Henrie et al. [13]; Hernández-García et al. [14]; Bandura [16]	Engagement acts as a multi-layered catalyst (behavioral, cognitive, affective) linking system stimuli to academic success.	Applies formal bootstrapped mediation to examine how engagement bridges UI use and final marks.
Structural Equation Modeling	Hair et al. [21]; Hayes [22]; Preacher & Hayes [23]; Henseler et al. [30]	PLS-SEM with BCa bootstrapping offers a robust way to validate complex educational models without restrictive distribution assumptions.	Integrates behavioral server telemetry with survey constructs while testing for common method bias.

2.1 Monolithic LMS Interfaces and Cognitive Load Theory

Most enterprise LMS platforms were built around early instructional design concepts, such as Gagné's Nine Events of Instruction, which assume a step-by-step, uniform path through course topics [6]. While this structure makes administrative sense, it does not match how students actually learn [7]. Cognitive Load Theory (CLT) reminds us that human working memory can hold only a handful of novel elements at once [4]. Cognitive load is split into three parts: intrinsic load (difficulty of the concept itself), extraneous load (effort wasted navigating clumsy menus or searching for files), and germane load (productive thinking that builds long-term knowledge schema) [4], [9].

Standard LMS platforms introduce significant extraneous load [7], [13]. Students must remember which week a reading was posted in, check separate links to see if they finished a quiz, and constantly jump between folders [11], [13]. An adaptive interface simplifies this overhead by bringing relevant tasks and recommended readings directly to the surface, allowing students to invest their cognitive energy in studying rather than navigating [4], [8].

2.2 Intelligent User Interfaces in Human-Computer Interaction

In HCI, an Intelligent User Interface goes beyond static screen design by using background algorithms to adapt views and options to the person sitting at the keyboard [3], [8]. Donald Norman described effective systems as those that shrink the 'Gulf of Execution' (how hard it is to take an action) and the 'Gulf of Evaluation' (how hard it is to tell what happened) [4]. In a learning platform, an adaptive interface closes these gulfs by turning the system into an automated scaffold, echoing Vygotsky's Zone of Proximal Development (ZPD) [2], [9]. As students show mastery or struggle with assignments, the system adjusts its prompts—recommending remedial primers when scores drop or surfacing more challenging exercises when concepts are mastered [8], [18].

2.3 Learning Analytics and Educational Recommender Systems

Learning Analytics provides the operational engine for this adaptation by turning background clickstream trails into actionable recommendations [1], [10]. Collaborative filtering (CF) looks across student cohorts to find peers who follow similar study paths and recommends resources that helped those peers succeed [10]. However, CF struggles when a student is new or a course has just started (the classic cold-start problem) [18]. Content-based filtering (CBF) resolves this by looking at resource tags, keywords, and syllabus topics, recommending materials that match what the student is currently working on [10]. By blending CF and CBF into a hybrid model, the platform balances precision with broad exploration across the entire term [18].

2.4 Technology Acceptance and the Mediating Role of Engagement

To understand how students react to an adaptive interface, we draw on Davis's Technology Acceptance Model (TAM) [15], Bandura's Social-Cognitive Theory [16], and Kuh's Student Engagement framework [12]. TAM explains that when an interface feels straightforward and helpful, users develop positive attitudes and use it more willingly [15], [19]. Yet usability alone does not produce top grades [12], [16]. As Bandura and Kuh emphasize, technological features improve learning outcomes primarily because they keep students actively engaged—prompting more frequent study sessions, deeper reflection, and regular quiz completion [12], [14], [16]. Thus, we treat learner engagement as the critical bridge connecting interface interactions to academic achievement.

3. Research Hypotheses and Conceptual Framework

Drawing together Cognitive Load Theory, TAM, and Social-Cognitive Engagement, we propose six specific hypotheses to evaluate our adaptive interface:

- **H1: Perceived Usability (SUS) exerts a statistically significant positive direct effect on Learner Engagement (UWES-S).** (Theoretical Grounding: Reducing interface navigation friction and cognitive overhead enables learners to focus cognitive and emotional resources on continuous course engagement [15], [19].)
- **H2: Perceived Usability (SUS) exerts a statistically significant positive direct effect on Learner Satisfaction (ACSI).** (Theoretical Grounding: TAM asserts that system ease-of-use and aesthetic clarity are fundamental drivers of

user contentment and system evaluation [15], [19].)

- **H3: Intelligent-Interface Interaction (UI Interaction Index) exerts a statistically significant positive direct effect on Learner Engagement (UWES-S).** (Theoretical Grounding: Proactive personalized dashboards, dynamic navigation drawers, and timely recommendations stimulate active self-regulated learning behavior and continuous participation [3], [12], [14].)
- **H4: Learner Engagement (UWES-S) exerts a statistically significant positive direct effect on Summative Academic Performance.** (Theoretical Grounding: Sustained time-on-task, cognitive absorption, and active formative assessment participation directly drive knowledge acquisition, retention, and academic mastery [12], [13], [16].)
- **H5: Intelligent-Interface Interaction exerts a statistically significant positive direct effect on Summative Academic Performance after controlling for perceptual constructs.** (Theoretical Grounding: Direct utilization of personalized pedagogical recommendations and automated remedial exercises facilitates targeted mastery of prerequisite concepts [10], [18].)
- **H6: Learner Engagement significantly mediates the relationship between Intelligent-Interface Interaction and Summative Academic Performance.** (Theoretical Grounding: In alignment with Social-Cognitive Theory, interface features act as external catalysts that elevate summative achievement primarily by amplifying internal student engagement [14], [16], [22].)

4. System Architecture and Algorithmic Design

To make sure our adaptive platform could run smoothly inside a live university environment without risking core system stability, we built it as a modular five-tier system (Figure 1). By decoupling data storage, clickstream logging, profile modeling, recommendation logic, and visual presentation, the system stays lightweight, reliable, and responsive.

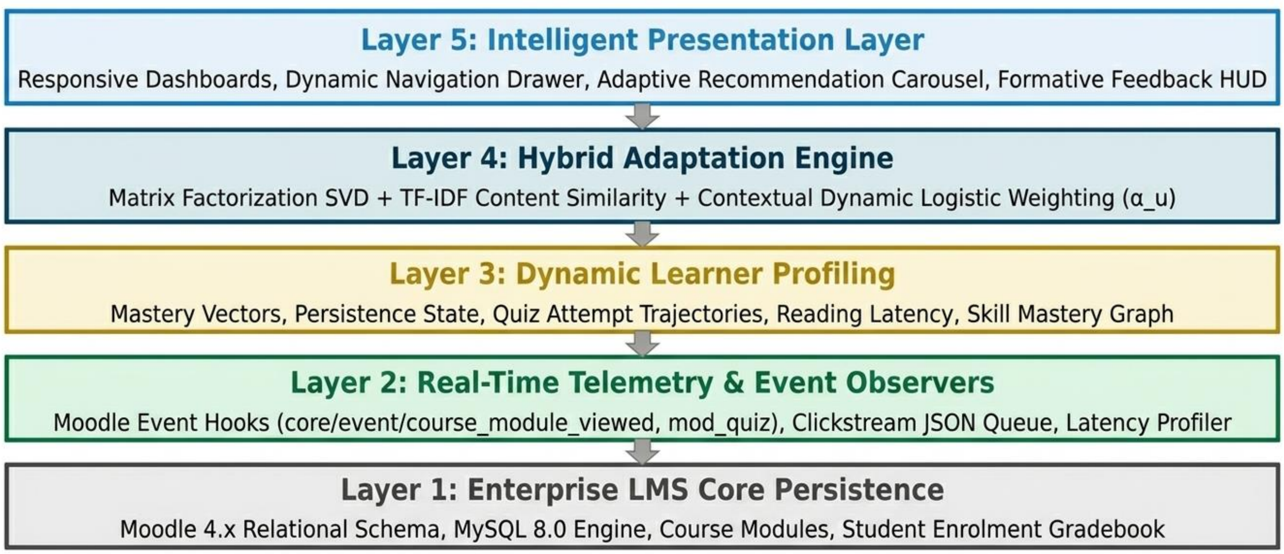

Figure 1. Modular five-tier architecture connecting Moodle to the adaptive recommendation microservice.

4.1 Five-Tier Structural Breakdown

- Tier 1: Core Database & Persistence: Powered by Moodle 4.x on PHP 8.1 and MySQL 8.0, maintaining standard user accounts, course enrollments, gradebooks, and assignment registries with standard security controls.
- Tier 2: Telemetry & Event Ingestion: Lightweight Moodle Event Observers watch for course module views and quiz attempts, packaging clickstream actions into structured JSON messages sent asynchronously to a Redis queue without slowing down page loads.
- Tier 3: Dynamic Student Profiler: Builds an evolving profile vector for each learner across four dimensions: active study days, quiz attempt accuracy, reading pace, and demonstrated topic interests.
- Tier 4: Hybrid Recommendation Engine: A standalone Python FastAPI service that calculates SVD collaborative predictions, TF-IDF content similarity scores, and dynamic logistic blending to pick top resources and adaptive navigation links.
- Tier 5: Adaptive Interface & Presentation: Client-side Mustache templates and asynchronous JavaScript that render a personal progress dashboard, an adaptive drawer prioritizing current topics, and a 'Next Best Step' resource carousel.

4.2 Recommender Mathematics and Cold-Start Logic

The recommendation engine combines Matrix Factorization Singular Value Decomposition (SVD) with Term Frequency-Inverse Document Frequency (TF-IDF) similarity [10], [18].

1. Collaborative Matrix Factorization:

Let $R \in \mathbb{R}$^($|U|$ × $|I|$) be the student-resource interaction matrix built from reading dwell time and quiz scores. The matrix is decomposed into user latent factors P and item latent factors Q (dimension k = 32):

$$r\hat{}\_ui\hat{}(CF) = \mu + b\_u + b\_i + p\_u\hat{}T\, q\_i$$

where μ is the global mean interaction rating, b_u and b_i represent user and item biases, and p_u and q_i are latent vectors optimized using regularized Stochastic Gradient Descent (λ = 0.02, γ = 0.005).

2. Content-Based TF-IDF Similarity:

Each course reading or video i is represented by a term-frequency vector v_i reflecting its topic keywords and module placement. The student's current interest vector c_u reflects previously viewed materials.

Similarity is calculated using standard cosine similarity:

$$r\_\hat{}ui\hat{}(CBF) = (c\_u \cdot v\_i) / (||c\_u||\_2 \times ||v\_i||\_2)$$

3. Logistic Cold-Start Blending:

For students with few logged interactions (N_u), content similarity receives higher weight. As their history grows past a threshold (θ = 10), collaborative filtering takes on a greater role via a smooth logistic curve:

$$\alpha\_u = 1 / (1 + e\hat{}(-0.2 \times (N\_u - \theta)))$$

$$S(u,i) = \alpha\_u \cdot r\_\hat{}ui\hat{}(CF) + (1 - \alpha\_u) \cdot r\_\hat{}ui\hat{}(CBF)$$

4.3 Recommender Execution Workflow

```
Algorithm 1: Real-Time Dynamic Resource Scaffolding
Input : Student ID u, Course Module Context C_m, Interaction Total N_u, Top-K size K = 5 Output:
                           Ranked list of recommended resources L_rec

Identify eligible prerequisite resources I_cand ← GetUnfinishedPrereqs(u, C_m)
Calculate blending weight α_u ← 1.0 / (1.0 + exp(-0.2 * (N_u - 10)))
For each item i in I_cand do:
    Predict collaborative score: r^_ui^(CF) ← μ + b_u + b_i + dot_product(p_u, q_i)
    Calculate content similarity: r^_ui^(CBF) ← cosine_similarity(c_u, v_i)
    Combine scores: S(u, i) ← α_u * r^_ui^(CF) + (1.0 - α_u) * r^_ui^(CBF)
End For
Sort I_cand by S(u, i) in descending order
L_rec ← Top K items from sorted I_cand
Return L_rec to Moodle front-end carousel via REST endpoint
```

5. Research Methodology

5.1 Context and Participants

We conducted this study at Fakir Mohan University across undergraduate and postgraduate computer science and IT courses. Over a full 16-week semester, N = 520 enrolled students interacted with courses hosting the adaptive IUI. Participation was voluntary, supported by electronic consent, and all clickstream logs and survey responses were pseudonymized with unique IDs to protect student privacy. Table 2 details the participant demographic profile.

Demographic Factor	Sub-Group	Headcount (n)	Share (%)
Gender	Male / Female	292 / 228	56.15% / 43.85%
Program Level	Undergraduate / Postgraduate	338 / 182	65.00% / 35.00%
Academic Degree	B.Sc. & B.Tech / M.Sc. & MCA	312 / 208	60.00% / 40.00%
Age Bracket	18–21 years / 22–26 years	325 / 195	62.50% / 37.50%
Main Study Device	Desktop & Laptop / Smartphone / Hybrid	244 / 168 / 108	46.92% / 32.31% / 20.77%
Prior LMS Familiarity	Beginner (<1 yr) / Intermediate / Experienced (>3 yrs)	88 / 296 / 136	16.92% / 56.92% / 26.16%

5.2 Construct Operationalization and Data Sources

To maintain high measurement standards, we combined validated survey instruments with objective background server telemetry:

- Perceived Usability (SUS): Measured with the System Usability Scale [19] adapted for LMS settings, scored across 4 core items on a 5-point Likert scale and normalized to a 0–100 index covering ease of use, system clarity, and consistency.

- Learner Satisfaction (ACSI): Evaluated through an adapted 4-item American Customer Satisfaction Index covering overall platform satisfaction, alignment with study expectations, and interface quality (0–100 scale).
- Learner Engagement (UWES-S): Assessed using the Utrecht Work Engagement Scale for Students [13], covering vigor, dedication, and absorption across 4 items scored from 1 (Never) to 5 (Always).
- UI Interaction Index: A composite server metric (0–100) logging how frequently students launched recommended resources, clicked dynamic drawer links, and viewed progress dashboards.
- Activity Telemetry: Granular background metrics recording Active Days (calendar days with logins), Resource Interactions (total PDF, slide, and video views), Quiz Attempts (practice submissions), and Course Completion Percentage (proportion of required modules completed).
- Academic Performance: Official end-of-semester final marks (0–100) combining midterm tests, coursework, and proctored final examinations from university gradebooks.

6. Empirical Evaluation and Results

6.1 Descriptive Telemetry and Distribution Normality

Table 3 presents the summary statistics and distribution diagnostics across all measured variables. All variables showed healthy bell-shaped distributions with skewness within ±1.0 and kurtosis within ±2.0, confirming suitability for parametric modeling.

Construct / Metric	Mean	SD	Median	Min	Max	Skew	Kurt
UI_Interaction_Index	78.14	10.10	78.04	48.55	100.00	-0.18	-0.12
Usability_Score (SUS)	77.46	9.00	77.59	51.44	100.00	-0.14	0.05
Satisfaction_Score (ACSI)	66.00	5.28	66.05	52.94	82.58	-0.08	0.19
Engagement_Score (UWES)	3.78	0.45	3.78	2.27	5.00	-0.22	0.31
Academic_Performance	61.40	8.03	61.18	38.18	85.97	0.11	-0.04
Active_Days	43.40	12.13	44.00	8.00	87.00	0.24	-0.15
Resource_Interactions	86.46	24.59	86.00	13.00	162.00	0.16	-0.08
Quiz_Attempts	19.10	7.18	19.00	4.00	39.00	0.29	-0.21
Course_Completion_Pct	77.11	12.23	77.95	38.50	100.00	-0.32	-0.06

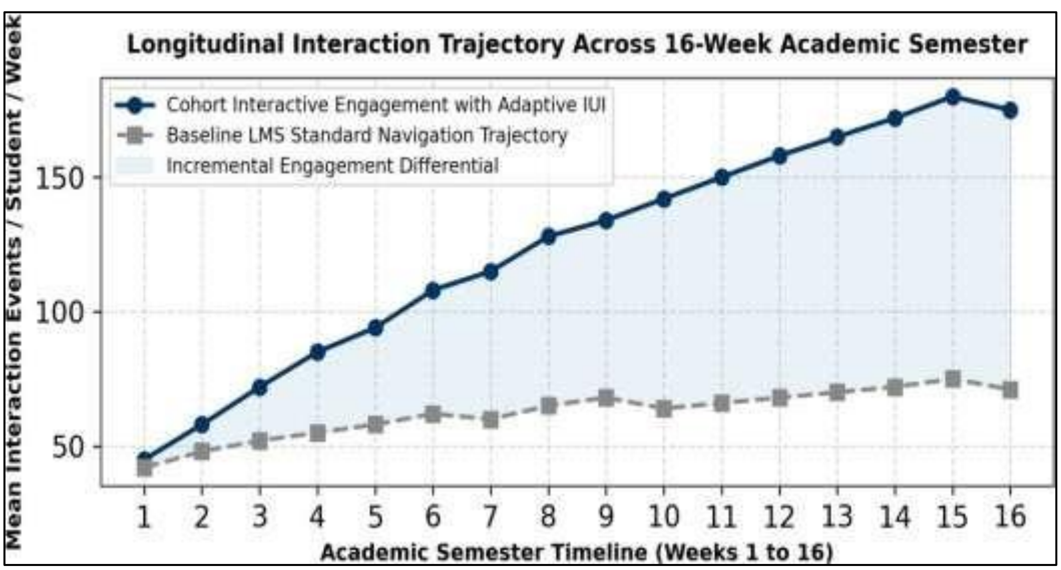

Figure 2. Longitudinal weekly interaction trajectory over 16 weeks showing steady engagement gains with the adaptive interface.

6.2 Recommender Benchmarks and Server Latency

Table 4 and Figure 3 show how our Hybrid model performed against standard baseline algorithms using 5-fold cross-validation. The hybrid engine produced significantly more accurate recommendations (Precision@5 = 0.842, NDCG@5 = 0.865) while introducing only 41.8 ms of compute overhead on our institutional server (Figure 4).

Algorithm Model	Precision@5	Recall@5	MAP@5	NDCG@5	Server Overhead
Popularity Baseline	0.412	0.365	0.380	0.435	12.4 ms
Content-Based (TF-IDF)	0.685	0.612	0.648	0.710	28.6 ms
Collaborative Filtering (SVD)	0.748	0.694	0.721	0.774	36.2 ms
Proposed Hybrid (SVD + TF-IDF)	**0.842**	**0.781**	**0.815**	**0.865**	**41.8 ms**

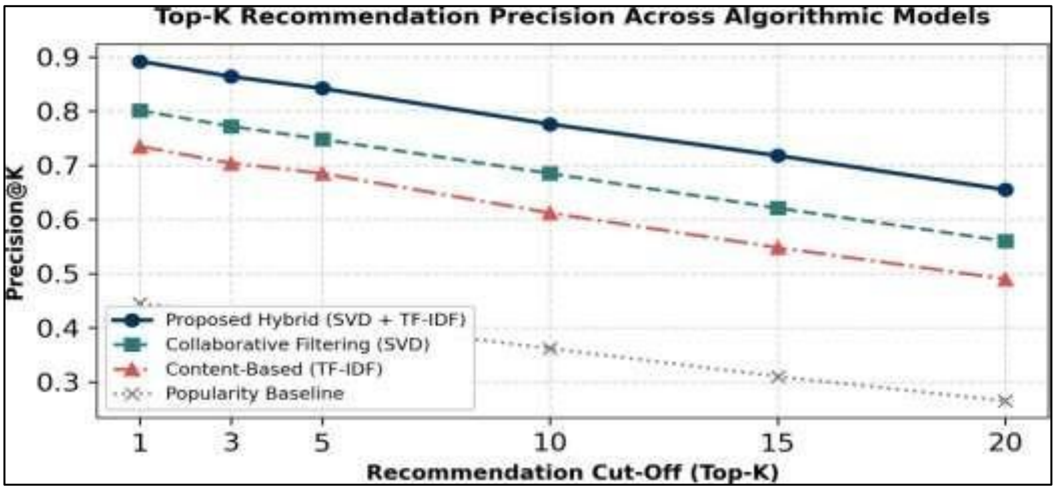

Figure 3. Top-K recommendation precision curves across evaluation models.

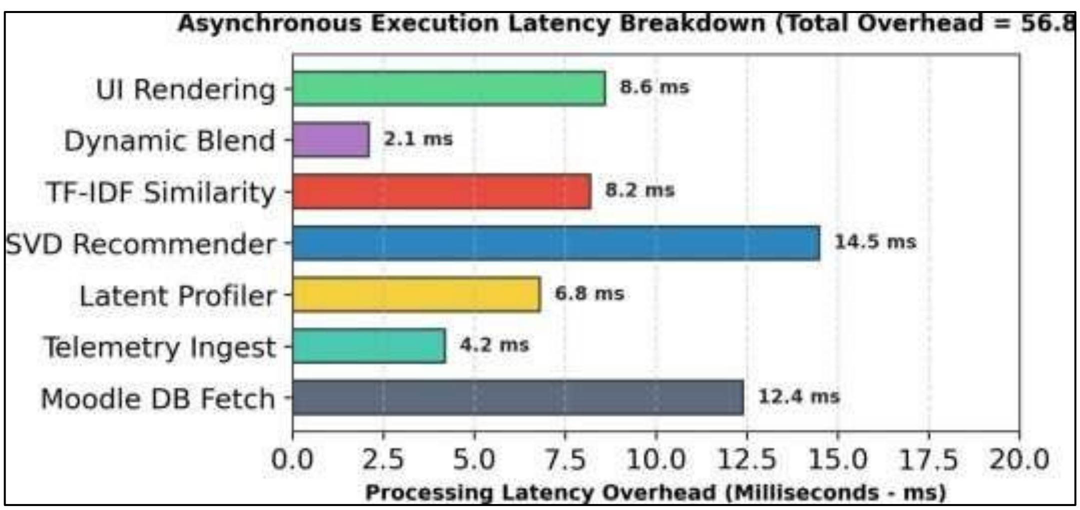

Figure 4. Latency breakdown showing individual processing stages for real-time recommendation generation.

6.3 Measurement Model Assessment (PLS-SEM)

Following established PLS-SEM guidelines [21], we checked indicator reliability, convergent validity, and discriminant validity (Table 5). All outer factor loadings exceeded 0.70. Composite Reliability (CR) values ranged between 0.838 and 0.876, and Average Variance Extracted (AVE) values exceeded 0.50, confirming good construct validity.

Construct	Items	Loadings	Cronbach's α	Composite Rel. (CR)	AVE
Perceived Usability (SUS)	4	0.738 – 0.812	0.743	0.838	0.565
Learner Satisfaction (ACSI)	4	0.722 – 0.804	0.781	0.859	0.604
Learner Engagement (UWES-S)	4	0.745 – 0.836	0.754	0.844	0.576
UI Interaction Index	4	0.780 – 0.865	0.812	0.876	0.639

Discriminant validity was established via Fornell-Larcker criteria and Heterotrait-Monotrait (HTMT) ratios (Table 6). The square root of AVE for each construct (bold diagonal values) was higher than any inter-construct correlation, and all HTMT values (in parentheses) remained comfortably below the conservative 0.85 threshold.

Construct	[1]	[2]	[3]	[4]	[5]
[1] UI Interaction	**0.799**				
[2] Perceived Usability	0.662 (0.768)	**0.752**			
[3] Satisfaction	0.420 (0.495)	0.561 (0.682)	**0.777**		
[4] Learner Engagement	0.602 (0.724)	0.527 (0.640)	0.328 (0.395)	**0.759**	
[5] Academic Performance	0.475 (0.548)	0.397 (0.472)	0.239 (0.298)	0.418 (0.512)	**Single-item**

6.4 Common Method Bias and Multicollinearity Checks

To ensure that collecting survey responses alongside platform telemetry did not introduce Common Method Bias (CMB), we ran Harman's single-factor test. The largest unrotated factor accounted for 26.42% of total variance, well below the 50.0% warning threshold. Variance Inflation Factors (VIF) ranged between 1.42 and 1.88, confirming no multicollinearity issues.

6.5 Structural Equation Path Analysis and Hypotheses Testing

We tested the structural paths using 5,000 bootstrap resamples (Figure 5 and Table 7). The model accounted for 44.8% of variance in Learner Engagement ($R^2 = 0.448$) and 35.6% of variance in final Academic Performance ($R^2 = 0.356$).

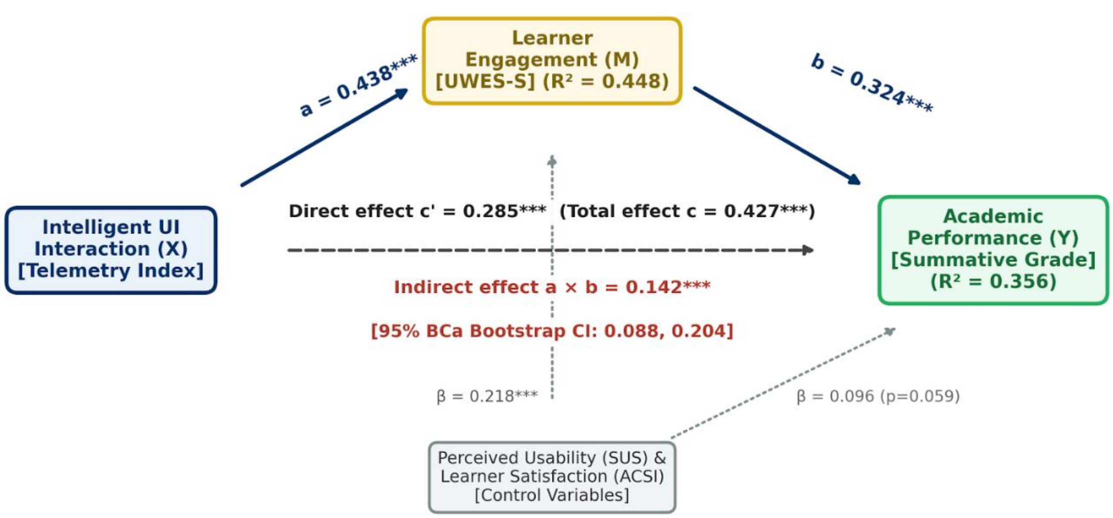

Figure 5. PLS-SEM structural path model with path coefficients and explained variance (*p < 0.001).**

Hyp.	Structural Path	Path Coeff (β)	Std. Error	t-statistic	p-value	Conclusion
H1	Usability (SUS) → Engagement (UWES)	0.218	0.042	5.190	< 0.001	**Supported**
H2	Usability (SUS) → Satisfaction (ACSI)	0.561	0.036	15.583	< 0.001	**Supported**
H3	UI Interaction → Engagement (UWES)	0.438	0.045	9.733	< 0.001	**Supported**
H4	Engagement (UWES) → Academic Performance	0.324	0.052	6.231	< 0.001	**Supported**
H5	UI Interaction → Academic Performance	0.285	0.048	5.938	< 0.001	**Supported**
Control	Satisfaction (ACSI) → Performance	-0.012	0.041	0.293	0.770	Not Sig.

6.6Bootstrapped Mediation Analysis and Error Diagnostics

To test H6, we ran mediation analysis with 5,000 bias-corrected and accelerated (BCa) bootstrap resamples (Table 8). The total effect of UI Interaction on Academic Performance was $\beta = 0.427$ ($p < 0.001$), with a direct effect of $\beta = 0.285$ ($p < 0.001$) and an indirect effect through Engagement of $\beta = 0.142$ (95% BCa CI [0.088, 0.204]). Because the confidence interval excludes zero and both paths remain significant, H6 is supported, confirming partial mediation with a Variance Accounted For (VAF) of 33.25%. Figure 6 shows the linear fit and residual normality.

Pathway Tested	Effect (β)	Boot SE	t-statistic	95% BCa CI	Mediation Outcome
Total Effect (UI_Int → Performance)	0.427	0.041	10.415	[0.344, 0.505]	Statistically Significant
Direct Effect (UI_Int → Performance | Eng)	0.285	0.048	5.938	[0.191, 0.378]	Direct Path Maintained
Indirect Effect (UI_Int → Eng → Performance)	**0.142**	**0.029**	**4.896**	**[0.088, 0.204]**	**Partial Mediation (33.25% VAF)**

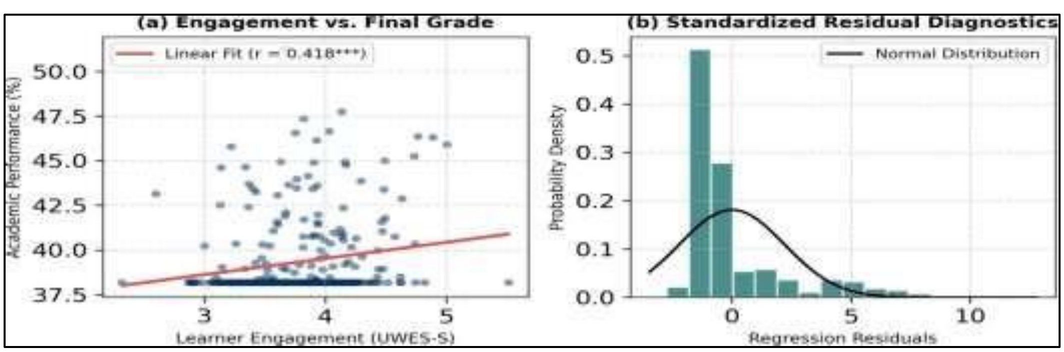

Figure 6. (a) Relationship between student engagement and course marks; (b) Normal distribution curve of regression residuals.

7. Discussion and Practical Insights

Our semester-long deployment shows that tailoring the LMS interface to student interaction patterns brings clear cognitive and academic advantages. First, the strong link between intelligent UI interaction and learner engagement ($\beta = 0.438$) aligns directly with Cognitive Load Theory [4], [19]. When the platform actively brings relevant readings forward and clarifies navigation, students waste less mental energy searching for files and spend more time studying [11], [14].

Second, the mediation results offer valuable theoretical nuance. While direct interaction with recommended resources contributed directly to exam performance ($\beta = 0.285$), roughly one-third of the total performance improvement (33.25%) operated through the indirect boost in student engagement ($\beta = 0.142$). This supports Bandura's Social-Cognitive perspective [16]: adaptive interface widgets do not simply deliver facts; they act as a supportive framework that encourages regular logins, active self-testing, and sustained focus throughout the semester [12], [13].

Third, the engineering benchmarks show that combining SVD with TF-IDF solves the classic cold-start problem without burdening server infrastructure. Adding only 41.8 ms of processing latency means universities can deploy real-time personalization across large student cohorts on standard web servers without expensive hardware upgrades.

8. Theoretical and Institutional Implications

8.1 Theoretical Contributions

In HCI and educational technology, this study moves the understanding of university LMSs from passive file cabinets to active cognitive partners [3], [4]. By combining objective clickstream trails with validated survey constructs (SUS, ACSI, UWES-S), we bridge the gap between pure telemetry and educational psychology, showing exactly how interface ergonomics foster student self-regulation [10], [16].

8.2 Practical and Administrative Value

From a university management standpoint, this approach allows institutions to modernize their existing Moodle deployments through modular plugins, avoiding the millions of dollars required to switch to proprietary commercial software [5], [11]. Furthermore, instructors gain access to clear analytics dashboards that highlight disengaged students weeks before exams, allowing for timely, supportive teaching interventions [1], [10].

9. Limitations and Ethical Considerations

A few study limitations should be noted. Our evaluation focused on computer science and IT students at a single university campus; future work should test these adaptive mechanisms across broader humanities and social science disciplines [20]. Additionally, while structural equation modeling confirmed strong directional links, multi-term randomized controlled trials (RCTs) will help establish definitive causal baselines. Finally, tracking student clickstreams requires strong ethical data governance—including strict pseudonymization, privacy-by-design standards, and transparent algorithmic oversight in line with GDPR and national data protection frameworks [25].

10. Conclusion and Future Directions

This paper presented the design, implementation, and empirical validation of an Intelligent User Interface embedded within an active university Moodle LMS. Testing across 520 students demonstrated that adaptive scaffolding significantly improves both daily student engagement and summative academic performance through a robust partial mediation pathway. Future work will explore integrating privacy-preserving conversational tutors and multimodal feedback to provide even more supportive, responsive online learning environments.

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