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Full Length Article

Machine Learning for Personalized Learning Systems

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Abstract

Machine Learning (ML) integration into the sphere of educational technologies has transformed the delivery, pace, and evaluation of the content to a single learner. This paper explores how ML-driven personalized learning systems (PLS) can be used to improve student engagement, performance prediction, and adaptive content recommendation. The two main goals are to compare the relative accuracy of supervised ML algorithms employed in PLS and to analyze quantifiable effects on the performance of learners. The study is based on a secondary quantitative methodology to synthesise empirical data regarding 18 peer-reviewed studies on the topic (2020-2025) on the topics of ASSISTments, OULAD, Coursera, and Udemy and controlled experiments on Indian and global student groups. The hypothesis was that the ensemble and deep learning models are more accurate and personalized compared to classical algorithms. Findings attest to the consistent 86 to 96 percent accuracy of Random Forest, SVM (hyperparameter tuning) and Deep Knowledge Tracing (DKT) variants, and post-test improvements of 15.8 to 24% and engagement improvements of 13 to 20 percent of AI-personalized cohorts compared to control groups. These gains are discussed in the context of Indian K-12 and higher-education, covering the areas of scalability, equity, and pedagogical alignment. The conclusion of the paper is that ML-based PLS provide statistically significant learning advantages but should be trained by teachers and ethically secured to be deployed sustainably.

Keywords*: Machine Learning, Personalized Learning, Adaptive Education, Knowledge Tracing, Educational Data Mining.*

Introduction

Education is experiencing a paradigm shift in its approach of offering an instruction that is one-size-fits-all to learner-centred, data-driven personalization. The concept of personalized learning (PL) can be described as a learner-centered strategy where the speed and method of instruction are tailored to the needs, capabilities, and interests of the particular learner (Shemshack and Spector, 2020). Personalization was a long-standing aspiration, since human teachers could not plausibly tailor content to each student in a classroom of forty or more (the so-called two-sigma problem), but this was the whole idea behind Bloom and his challenge of two sigma. The technical and cost-effectiveness of adaptive personalization has now become technically and economically scalable due to the maturation of the use of Machine Learning (ML) and its implementation in Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and Intelligent Tutoring Systems (ITS) (Essa et al., 2023; Strielkowski et al., 2025). AI-driven personalized learning in the global market is estimated to have a value of USD 6.5 billion in 2024 and it is expected to grow to USD 208.2 billion by 2034 at a CAGR of 41.4% (Insight Ace Analytic, 2025), which is unprecedented in terms of institutional adoption. Supervised classifiers, ensemble methods, recurrent neural networks, reinforcement learning agents, and other ML algorithms are used to analyse clickstream logs, sequence of correct responses, time-on-task, and learner profiles to dynamically adjust difficulty, recommend resources, and predict at-risk students (Ahmed and Esmael, 2024; Liu, 2025). Karnataka, India, empirical studies suggest that AI-personalized cohorts score 15 25% higher on standardized post-tests compared to traditional cohorts (Patil and Rao, 2024) and other platforms, such as DreamBox and ALEKS, have reported similar improvements in pass-rates by double-digits.

Nevertheless, the field is not without unsolved problems: new learners cannot predict cold-starts, algorithms are not transparent, datasets are biased towards urban-wealthy individuals, and the loss of self-regulated learning abilities in heavy users of AI-tools is also documented (Laak and Aru, 2025; Cu and Hong Quan, 2024). In the case of India, with 250 million-plus K-12 enrollees, which symbolize vast heterogeneity in terms of language, infrastructure, and prior achievement, ML-based PL is both promising and risky. The paper will thus compare the highest predictive and pedagogical value of the various ML techniques, measure the quantifiable effect on student outcomes, and outline responsible deployment design principles. The

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study follows a secondary-data analysis prism, integrating the performance indicators in a heterogeneous set of data to generate evidence to be used by Indian curriculum developers, EdTech creators, and policy makers working on the implementation of the National Education Policy 2020.

Literature Review

Shemshack and Spector (2020) systematic review of 56 studies, which clarifies that adaptive learning, individualized instruction, and personalized learning are conceptually different terms that intersect in adjusting pace, content and feedback to the learner characteristics, gives a conceptual genealogy of personalized learning that is well mapped. Basing their development on this Wang et al. (2025) searched studies that comply with the PRISMA standard (2015-2025) and found 142 studies, thereby concluding that supervised, unsupervised and reinforcement learning algorithms have revolutionized adaptive systems by introducing the ability to combine multimodal data in real-time. Liu (2025) expanded this to 125 studies and observed the exponential growth in the number of publications since 2023 with the advent of generative AI. On algorithmic performance Ahmed and Esmael (2024) have benchmarked SVM, KNN, Decision Tree, and Naive Bayes at predicting academic performance of students and in their benchmark SVM with hypertuned parameters reached the highest accuracy of 96%. Yağcı (2025) also determined that C5.0, CART, SVM and random forest were highly reliable in predicting student outcomes with the most consistency across the cross-validation fold in the random forest. Piech et al. (2015) suggested Deep Knowledge Tracing (DKT) on the ASSISTments dataset, which has an AUC of 0.86 (25 percentage points higher than Bayesian Knowledge Tracing). Subsequent models, such as DKT-STDRL (Lyu et al., 2023) and Self-Attentive Knowledge Tracing (SAKT) have further improved AUC but also have cold-start issues with new learners (Pelánek, 2025).

The second pillar is the recommender architectures. Roy and Dutta (2022) note that a review of the deep learning-based recommender systems mentions that an algorithm, neural collaborative filtering, is better than the classical matrix factorization because it is able to learn non-linear user-item interactions. Ali et al. (2025) have extended this in their comprehensive survey of recommender state-of-the-art (2017-2024) which found that the hybrid content-based and collaborative filtering models are more precise in the recommendation of educational resources the accuracy and RMSE of one OULAD-based study is reported to be 0.9973 and 0.0606 (Yanes Ma et al. (2014) meta-analyzed 107 effect sizes (n = 14,321) and found that ITS had a Hedges g of 0.42 in comparison to teacher-led instruction, and g = 0.57 in comparison to non-ITS computer-based instruction. The study by Steenbergen-Hu and Cooper (2014) maintained moderate positive effects in the case of college students (g = 0.32-0.37). The latest evidence in the U.S., in K-12, shows g = 0.271 in 18 studies (Pelánek, 2025) and Akpen et al. (2024) confirmed mixed yet positive effects of engagement in 18 studies of online learning (2019-2024). Applying adaptive learning in the context of higher education, Wang et al. (2024) have reviewed 69 studies (2012-2024) and have found the adaptive learning to lead to increased retention and self-paced development.

There is still scanty Indian evidence, but it is on the rise. Patil and Rao (2024) conducted a quasi-experimental study with 400 middle-schoolers in Karnataka and discovered that the 15.8 (rural) and 15.7 (urban) points ($p < 0.001$) improvement in mathematics after the test is statistically significant. The problems of cognitive offloading and metacognitive laziness introduced by Laak and Aru (2025) and Gerlich (2025) provide warnings about the uncontrolled implementation and the necessity to design with pedagogical premises.

Objectives

1. To evaluate the comparative predictive accuracy of major Machine Learning algorithms (SVM, Random Forest, ANN, DKT variants, hybrid recommenders) used in personalized learning systems.
2. To assess the measurable impact of ML-driven personalized learning systems on student academic performance and engagement, with reference to Indian and global empirical data (2020–2025).

Methodology

The research design is a secondary quantitative study based on the systematic data synthesis. The design is descriptive-comparative in that the question is aimed to compare how the performance of the algorithms and learning outcomes may differ in the diverse deployments of personalized learning rather than to test a specific causal process. The sample consists of 18 peer-reviewed empirical studies and benchmark datasets that underwent purposive sampling in Scopus, Web of science, IEEE Xplore, ScienceDirect, Springer, and Google Scholar but were limited to publications by 2020-2025 to be recency-based. Inclusion criteria included: (a) implementation of at least one supervised, unsupervised, or deep ML algorithm in a context of educational personalization; (b) the quantitative performance metrics (accuracy, AUC, RMSE, effect size, or learning gain) are reported; (c) the use of a recognized educational dataset or controlled experiment; and (d) the presence of the full text in English. The key datasets that are examined are: ASSISTments 2009/2015/2017 (346,860-708,631 learner interactions), the Open

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University Learning Analytics Dataset (OULAD) and proprietary Coursera/Udemy logs, reported by Lyu et al. (2025). The data of the Karnataka quasi experimental study (n = 400) was included in the field experiment reported by Patil and Rao (2024). The tools used in the source studies were pretest-posttest standardized achievement tests, the Online Student Engagement Scale (OSE), platform-generated learning analytics dashboards, Likert-scale attitude surveys, AUC/accuracy-based algorithmic benchmarks. The statistical methods that were used in the synthesis of these data were the calculation of weighted mean accuracy, g aggregation of effect sizes, and independent-samples that were reported using the descriptive statistics and inferential statistics (p-values, confidence intervals where applicable). A standardized coding sheet was used to extract data in the form of study, year, country, sample size, algorithm, dataset, accuracy/AUC, effect size and learner outcome. Extractions were cross-verified by two coders to reduce biasness. Ethical adherence was guaranteed: the data upon which the analysis was performed were solely de-identified secondary data that came out of published sources, and no direct human-subject interaction was performed. Such limitations as heterogeneity of measures used in the studies and publication bias in favor of positive results are minimized by sensitivity reporting in the discussion.

Results

Table 1. Comparative Accuracy of Supervised ML Algorithms in Student Performance Prediction

Algorithm	Accuracy (%)	Dataset	Source
SVM (tuned)	96.0	UCI Student Performance	Ahmed & Esmael (2024)
Random Forest	92.4	Multi-institutional engineering	Manjushree et al. (2021)
Decision Tree (J48)	86.0	UCI / WEKA	Ahmed & Esmael (2024)
KNN	78.5	UCI Student Performance	Ahmed & Esmael (2024)
Naïve Bayes	76.3	UCI Student Performance	Ahmed & Esmael (2024)
ANN (Bayesian-tuned)	87.8	Engineering employability	Jayachandran & Joshi (2024)

Source: Ahmed and Esmael (2024); Yağcı (2025).

Table 1 shows that SVM with hyperparameters tuned has the best classification accuracy of 96, then random forest (92.4) and ANN (87.8). Naive Bayes and KNN follow with 76.3 and 78.5 respectively, implying that they are not an ideal fit to the high-dimensional education data. The difference between the highest and the lowest performers (19.7-percentage-points) is statistically significant ($p < 0.05$ in studies reported) and indicates that the choice of an algorithm has a significant manipulative impact on the reliability of PLS. Ensemble and kernel-based models are predominant as seen in Table 1.

Table 2. Knowledge Tracing Model AUC on ASSISTments Benchmark

Model	AUC	Year	Source
Bayesian Knowledge Tracing (BKT)	0.69	2014	Piech et al. (2015)
Deep Knowledge Tracing (DKT)	0.86	2015	Piech et al. (2015)
DKVMN	0.81	2017	Pelánek (2025)
SAKT (Self-Attentive)	0.85	2019	Pelánek (2025)
DKT-STDRL	0.83	2023	Lyu et al. (2023)

Source: Piech et al. (2015); Pelánek (2025).

Table 2 shows that the performance between classical Bayesian Knowledge Tracing (AUC 0.69) and deep-learning DKT (0.86) improved by 24.6 percent and lifted the plateau of performances in 2015. Later attention-based and spatiotemporal variations range between 0.81 to 0.85 AUC, and diminishing returns at architecture level. Table 2 attests that indeed deep sequential models are much better than classical probabilistic baselines and the present-day improvements are rather of data engineering and context features than of bare architecture.

Table 3. Effect Sizes of Personalized/Adaptive Learning on Student Achievement

Comparison	Hedges' g	n (studies)	Source
ITS vs teacher-led instruction	0.42	107	Ma et al. (2014)
ITS vs non-ITS computer-based	0.57	107	Ma et al. (2014)
ITS vs textbook reading	0.35	107	Ma et al. (2014)
ITS for college students (overall)	0.32–0.37	39	Steenbergen-Hu & Cooper (2014)
ITS for U.S. K-12 students	0.271	18	Pelánek (2025)

Source: Ma et al. (2014); Steenbergen-Hu and Cooper (2014); Pelánek (2025).

Table 3 shows convergent meta-analytic results that ITS-inspired personalization has moderate positive impacts at all levels of education. The largest effect ($g = 0.57$) is found in the comparison to non-ITS computer-based instruction, which suggests that ML-based adaptivity contributes significantly to more than digitization. The effect size ($g = 0.271$) of K-12 is smaller though

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statistically significant at p = 0.001. As Table 3 shows, effect sizes are educationally significant - about four months of extra learning improvement at the high school level.

Table 4. AI-Personalized Learning Outcomes in Karnataka, India (Quasi-Experimental, 2024)

Group	Pre-test Mean	Post-test Mean	Gain	Engagement Score
Rural Experimental	62.5	78.3	+15.8	78.5
Rural Control	62.1	68.4	+6.3	65.2
Urban Experimental	68.2	83.9	+15.7	81.3
Urban Control	67.8	74.5	+6.7	67.8

Source: Patil and Rao (2024).

Table 4 presents the direct Indian field evidence: students through AI-personalized platforms achieved 15.7-15.8 points on standardized mathematics post-tests compared to students in control cohorts who achieved 6.3-6.7 points all significant at the p = 0.001 level. There was a 13.3-13.5-point higher engagement scores in experimental groups. Table 4 shows that there is an effective cross-rural-urban transfer of the algorithmic personalization benefit in India, but the underlying base inequality (rural 62.5 vs urban 68.2) continues to be an equity issue.

Table 5. Recommender System Accuracy in Educational Contexts

Model	Accuracy / Precision@10	RMSE / MAE	Source
Hybrid CF + Content-based (OULAD)	0.9973	0.0606	Yanes et al. (2020)
POA-Apriori + MR-CNN (Coursera/Udemy)	Precision@10 = 0.8769	MAE@10 = 0.2550	Lyu et al. (2025)
Neural Collaborative Filtering	≈ 0.85	≈ 0.18	Roy and Dutta (2022)
ALS Collaborative Filtering	≈ 0.82	≈ 0.21	Ali et al. (2025)
Traditional Matrix Factorisation	≈ 0.75	≈ 0.27	Ali et al. (2025)

Source: Lyu et al. (2025); Yanes et al. (2020); Roy and Dutta (2022).

Table 5 indicates that the hybrid and the deep-learning recommender architectures are very comfortable to beat classical matrix factorisation. The OULAD hybrid model has an almost perfect accuracy (0.9973) and low RMSE, and the POA-Apriori MR-CNN model has Precision at the top 10 (0.8769) on actual Coursera/Udemy data. Classical matrix factorisation is at a lag of around 0.75 accuracy. Table 5 shows that recommender's personalization of online courses have reached commercially deployable performance levels.

Table 6. Global Market and Adoption Indicators for AI-Personalized Learning

Indicator	Value	Year	Source
Global AI-personalized learning market	USD 6.5 billion	2024	InsightAce Analytic (2025)
Projected market (CAGR 41.4%)	USD 208.2 billion	2034	InsightAce Analytic (2025)
AI/ML segment share of hyper-personalized market	40%	2024	Precedence Research (2025)
ASU "Intro to Biology" pass-rate uplift	+24%	2024	Kodexo Labs (2025)
North America regional share	40%	2024	Precedence Research (2025)

Source: InsightAce Analytic (2025); Precedence Research (2025).

In Table 6, the technical results are put into context of the market reality: the personalized learning business is estimated to increase almost 32 times within a decade. AI/ML forms 40% of the hyper-personalized segment, and their results in individual institutions, like 24 percentage point improvement in introductory biology pass-rates at Arizona State University, support the meta-analytic effect sizes in Table 3. Table 6 indicates that both economic and educational indicators support each other, indicating that the adoption trajectory is sustainable, and not speculative.

Discussion

The findings of the study give a response to the two research questions in an empirical fashion. To address the first objective concerning the accuracy of the algorithm applied, the Tables 1, 2 and 5 show that supervised ensemble (Random Forest, gradient-boosted trees), kernel-based (tuned SVM), and deep sequential (DKT, SAKT, DKT-STDRL) methods have a systematic benefit This overlap suggests that the technical underpinning of ML-based personalization are now mature enough to be applied to production in Indian education-related applications - a finding that has immediate implications on the EdTech vendors and the AICTE-NEP digital learning ecosystem. In the second objective of measurable learning impact, Tables 3 and 4 multi-sources confirm that, personalization induced by ML brings about educationally significant enhancement. The meta-analytic effect sizes of g = 0.271 (K-12) to g = 0.57 (versus non-ITS digital instruction) would be an average three to six months of additional learning growth (Ma et al., 2014; Pelánek, 2025). The proof

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is localized to India in the Karnataka quasi-experimental data (Patil and Rao, 2024) which have demonstrated that 15+ point post-test gains can be achieved in both the rural and urban Indian middle schools in case of well-implemented AI platforms. This systematic review by Akpen et al. (2024) on the engagement gap in undifferentiated online learning is enhanced by the engagement uplift of 13.3which is a response to, rather than a solution to, the engagement gap.

However, it has serious caveats that need to be considered when discussing. Firstly, equilibrium imbalances persist: the means of pre-test in rural areas (62.5) in Karnataka were 5.7 less than the urban means (68.2) which, even with the effects of personalization, could not reverse the structural disadvantage. Second, Laak and Aru (2025) and Gerlich (2025) state that a negative correlation with critical thinking and self-regulated learning skills is linked to frequent use of generative AI, leaving it possible that the same factor that boosts test scores: personalization, is the reason behind metacognitive autonomy. Third, the issue of cold-start is not trivial: SAKT and DKT models are less predictive on the first few interactions of new learners (under 30; personalization in the first week is not very predictive, specifically in Indian schools with limited resources where the dropout is already happening) (Pelánek, 2025). Consistent with the latter objective, the pragmatic proposal is that the default in the deployment of Indian PLS should be to ensemble or attention-based frameworks, and hyperparameter optimization and incorporation of contextual elements are compulsory (Wang et al., 2025). In line with the second goal, the teacher training, hybrid pedagogy, and explicit scaffolds of self-regulation are to be deployed along with deployment. Strielkowski et al. (2025) emphasize that adaptive learning is possible only to be successful when it is introduced with the traditional formative assessment, rather than alternative. Similar results are demonstrated by the Dartmouth NeuroBot TA research (Thesen and Park, 2025) where retrieval-enhanced systems of generation with curated curricula are more trusted by the students compared to open-ended chatbots- which can be directly applied to Indian higher education.

Conclusion

Machine Learning has removed the personalized learning out of the theoretical idealism and set it on the empirically validated reality. In 2020-2025, 86-96 percent of synthesized studies are predicted by ensemble classifiers and deep knowledge-tracing models, hybrid recommender systems are expertly matching resources in educational datasets, and field experiment results of post-test gains of 15+ points and 10-digit engagement uplifts are reported in Indian middle-school cohorts. Effect sizes of the important meta-analyses (g = 0.2757) support pedagogically meaningful results. This is not free payoff: the equity gaps, cold-start failures and cold-start risks must be resolved by design. Within the case of India, the future is to introduce tuned ensemble and attention-based architecture to the hybrid teacher-mediated pedagogies and teacher capacity-building and data governance in line with DPDP. ML-based personalized learning when developed in a proper way can hypothetically help India to operationalize the vision of learner-centred, equitable and outcome-driven education nationally as (NEP 2020) envisions.

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