Meta-model for Recommendation of Machine Learning Algorithm in Education

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Abstract

The increasing use of artificial intelligence (AI) and machine learning (ML) in education has created the need for clear guidance on selecting appropriate algorithms for specific educational tasks. Educational datasets differ considerably in size, structure, and pedagogical context, while machine learning algorithms vary in complexity, interpretability, and practical feasibility. Consequently, educators and researchers- particularly those without strong technical backgrounds- rely on trial-and-error approaches, which can result in inefficient or poorly justified analytical choices. This paper proposes an explainable meta-model for recommending machine learning algorithms in educational settings. The approach is grounded in meta-learning and focuses on capturing relationships between dataset characteristics and algorithm performance. Four classification methods-Ridge Classifier, Decision Tree Classifier, Multilayer Perceptron, and K-Nearest Neighbors-were used to develop and evaluate the meta-model across 15 educational datasets. Model performance was assessed using multiple metrics relevant to educational decision-making, including accuracy, precision, recall, F1-score, Cohen's kappa, and computational time, alongside a cross-validation strategy to ensure robustness. The results highlight important trade-offs between predictive accuracy, reliability, interpretability, and efficiency. While more complex models achieved higher accuracy, simpler and more transparent approaches demonstrated more balanced performance and greater practical suitability for educational and policy-oriented contexts. These findings reinforce the value of context-aware algorithm selection rather than reliance on single performance metrics. The proposed meta-model offers practical support for educators and policy makers by reducing experimentation costs and enabling evidence-based decision-making. By bridging algorithmic complexity and educational needs, this research contributes a generalizable and interpretable framework that promotes trustworthy use of machine learning in education.

Keywords: artificial intelligence, machine learning, educational data mining, meta-model, recommender system, predictive models, classification, algorithm selection.

1. Introduction

The use of machine learning (ML) and artificial intelligence (AI) in education has grown rapidly over the past decade, influencing areas such as student assessment, learning analytics, curriculum design, and institutional decision-making. Educational institutions increasingly rely on data to better understand learning processes, identify students at risk, and support more personalized and inclusive educational practices. While these developments offer significant potential benefits, they also introduce new challenges, particularly for educators, researchers, and decision-makers who may not have a technical background in AI and ML.

One of the key challenges lies in selecting appropriate ML algorithm for educational purposes. Different machine learning algorithms are designed to work best under specific conditions, depending on factors such as the size of the dataset, the type of educational task, and the nature of the data being analyzed. In practice, however, the choice of algorithm is often driven by convenience, prior familiarity, or popular trends rather than by systematic evidence. This can lead to models that are difficult to interpret, insufficiently justified, or misaligned with educational goals and ethical considerations.

From an educational perspective, algorithm selection should not be viewed as a purely technical decision. Instead, it should be understood as part of a broader pedagogical and organizational context, where transparency, accountability, and trust are essential. Educators and educational researchers need tools and frameworks that help them make informed choices without requiring deep expertise in computer science, artificial intelligence, machine learning or advanced mathematics. In this sense, there is a growing demand for approaches that bridge the gap between complex machine learning techniques and the practical realities of educational research and practice.

This paper addresses this gap by proposing a meta-model for recommending machine learning algorithms in education. Rather than focusing on the internal technical details of algorithms, the proposed approach emphasizes relationships between educational data characteristics and observed outcomes. By learning from previous applications of machine learning in education, the meta-model provides guidance on which types of algorithms are likely to be most suitable for particular educational tasks. Importantly, the recommendations are designed to be explainable and understandable, allowing users to see why a specific approach may be appropriate in a given context.

By adopting a cross-disciplinary perspective, this study aims to support evidence-based and responsible use of machine learning in education. The proposed meta-model contributes to more transparent decision-making, reduces reliance on trial-and-error experimentation, and empowers educators to engage more confidently with data-driven educational innovation.

This paper is structured as follows. Section 2 provides a scoping literature review on the given topic. Section 3 explains methodology, while section 4 gives research results. Section 5 discusses research results along with the implications and limitations. Section 6 concludes the paper providing guidelines for further research.

2. Related work

This scoping review of studies in a span from ten years (2016-2025) examining machine learning algorithm application in educational contexts reveals that supervised learning approaches dominate, with Decision Trees (19 instances), Long Short-Term Memory networks (16 instances), and Random Forest (16 instances) appearing most frequently. Table 1 provides overview of related studies, providing information about educational level, type of the educational problem and machine learning algorithm which was applied to solve given problem.

Table 1. Overview of related studies on machine learning applications in education

Study	**Educational Level**	**Educational Problem**	**Primary ML Algorithms**
[1]	Higher education	Performance prediction, at-risk student identification	DT, SVM, NB, ENS
[2]	K–12 and higher education	Performance prediction, at-risk student identification	SVM, ANN, DT
[3]	Not specified	Student performance prediction	DT, LSTM, RF, KNN, NB, SVM, LR, ANN, CNN, XGB
[4]	MOOCs (higher education / professional training)	Knowledge tracing, performance prediction	Not specified
[5]	Higher education and MOOCs	Course recommendation and career guidance	KNN, RF, SVM, NB, DL, TR
[6]	Higher education or professional training	Performance prediction	Not specified
[7]	Higher education	Performance prediction, at-risk student identification	LR, ANN, ENS
[8]	Higher education or professional training	Student academic performance prediction	DT, ANN, SVM, LR, NB, RF
[9]	Not specified	Performance prediction and optimization	SVM, FCM, DL
[10]	General educational context	Personalized content filtering for teaching and learning	CF, CBF, KBF, HYB
[11]	Higer education	Dashboard for students	RF
[12]	Higer education	Performance prediction	DT, ANN

*Machine Learning Algorithms abbreviations: *ANN – Artificial Neural Networks, CBF – Content-Based Filtering, CF – Collaborative Filtering, CNN – Convolutional Neural Networks, DL – Deep Learning, DT – Decision Trees, ENS – Ensemble Methods, FCM – Fuzzy C-Means, HYB – Hybrid Recommender Approaches, KBF – Knowledge-Based Filtering, KNN – K-Nearest Neighbor, LR – Logistic / Linear Regression, LSTM – Long Short-Term Memory Networks, NB – Naive Bayes, RF – Random Forest, SVM – Support Vector Machine, TR – Transformer Models, XGB – Extreme Gradient Boosting (XGBoost)*

2.1. Educational Context and Pedagogical Alignment

The application of machine learning in education predominantly targets personalized learning and adaptive educational interventions. Studies emphasized personalization as a core pedagogical approach, with recommender systems designed to recognize individual preferences and constraints. The incorporation of domain-specific knowledge varied considerably across implementations. Some studies integrated prerequisite knowledge and curriculum structure into their models, while others focused primarily on demographic, academic, and behavioral features without explicit pedagogical frameworks.

Learning theories and educational frameworks were notably underrepresented in the technical literature. Only one study explicitly referenced educational theory, mentioning Felder's learning style theory. Most implementations focused on predictive accuracy without grounding their approaches in established learning theories. Knowledge tracing applications incorporated learner models to track student mastery, representing one of the few areas where educational domain knowledge was explicitly embedded in the technical architecture.

Stakeholder perspectives reflected different priorities across studies. Student-centered approaches dominated course recommendation systems, while performance prediction systems served institutional needs for identifying at-risk students. Educational institutions showed interest in these systems for improving retention and success rates, though educator perspectives on pedagogical integration remained largely unexplored.

2.2. Algorithm Selection Patterns and Educational Applications

Supervised learning approaches dominated across all educational applications, with classification and regression tasks representing the primary use cases. For performance prediction tasks, Decision Trees appeared most frequently with 19 instances, followed by Long Short-Term Memory networks and Random Forest with 16 instances each. Traditional algorithms like K-Nearest Neighbor (12 instances) and Naive Bayes (11 instances) remained prevalent, suggesting preference for interpretable models in educational settings.

Support Vector Machines emerged consistently across multiple reviews as effective for educational prediction tasks, with one study identifying SVM as among the best techniques for predicting input-output parameters in e-learning models. Neural network approaches, including Artificial Neural Networks and Convolutional Neural Networks, appeared less frequently but showed promise for handling complex patterns. Deep learning algorithms produced better results specifically for large datasets, though their adoption remained limited relative to traditional methods.

Ensemble learning techniques featured prominently across studies, suggesting recognition of the value in combining multiple models to enhance prediction accuracy. For recommendation systems, the algorithmic landscape differed, with K-Nearest Neighbor and Random Forest representing the most commonly deployed traditional algorithms. Hybrid approaches combining collaborative filtering, content-based filtering, and knowledge-based strategies emerged as effective for educational recommender systems.

The rationale for algorithm selection emphasized high interpretability and low computational cost, reflecting the practical constraints of educational environments where model transparency matters for stakeholder acceptance. Studies seeking to predict student outcomes prioritized accuracy metrics, while those addressing personalized learning also considered the relevance of recommendations.

2.3. Performance Evaluation and Validation

Evaluation metrics showed considerable diversity across studies, reflecting different educational objectives. For classification tasks predicting student outcomes or categorizing learners, accuracy, precision, and recall emerged as primary metrics. One study identified significant positive impacts in 36 cases using chi-square tests to establish statistical associations between ML interventions and student outcomes, with p-values of approximately 0.0093. Regression metrics including Mean Absolute Error, Mean Square Error, Root Mean Square Error, and R-squared appeared in continuous prediction contexts.

For recommendation systems, evaluation frameworks expanded beyond accuracy to include ranking-based metrics such as hit rate, Normalized Discounted Cumulative Gain, and Mean Average Precision. F1-score gained prominence for handling imbalanced educational datasets where minority classes (such as at-risk students) held particular importance. However, the lack of standardized evaluation approaches across studies limited meaningful comparisons. Studies deployed primarily in e-learning environments raised concerns about generalizability to traditional educational contexts.

Cross-validation approaches and statistical significance testing remained underreported across most reviews. Only one study explicitly discussed pairwise comparisons with adjusted p-values to assess differences in positive impacts among machine learning types. The absence of rigorous validation frameworks represented a significant methodological gap, particularly given the high-stakes nature of educational decision-making.

2.4. Algorithm recommendations

Machine learning algorithm effectiveness depends critically on context-specific factors rather than universal superiority: deep learning methods excel with large datasets , while traditional algorithms like K-Nearest Neighbor and Decision Trees perform better with the small sample sizes that characterize most educational implementations. From an educational perspective, the literature demonstrates a problematic gap between technical optimization and pedagogical considerations. Educational theories and learning frameworks remain largely absent, with only one study explicitly referencing educational theory. Algorithm selection prioritizes interpretability and low computational cost over marginal accuracy gains, reflecting practitioners' need for transparent, actionable insights rather than black-box predictions. The evidence suggests that recommending algorithms for educational contexts requires balancing multiple factors: dataset size and quality, educational application type (performance prediction vs. recommendation vs. knowledge tracing), stakeholder interpretability needs, and deployment environment (e-learning vs. traditional classroom).

A meta-model for algorithm recommendation must account for these educational constraints rather than relying solely on predictive performance metrics, though current literature provides limited empirical guidance for systematically weighing these competing considerations.

3. Methods

This study employs a meta-learning methodology to develop a meta-model for recommending machine learning algorithms in educational contexts. The methodological design is informed by the need for reliability, transparency, and practical relevance, particularly for users without advanced technical expertise. The selected methods and evaluation procedures were chosen to balance predictive performance with interpretability and real-world applicability in educational settings.

3.1. Meta-model development

The meta-model is built using four complementary classification methods: Ridge Classifier, Decision Tree Classifier, Multilayer Perceptron (MLP) Classifier, and K-Nearest Neighbors (KNN) Classifier. These models were selected to reflect different analytical perspectives and to ensure that the meta-model can capture a wide range of relationships between educational data characteristics and algorithm performance.

The Ridge Classifier represents a regularized linear approach that is particularly well suited for educational datasets where features may be correlated or where sample sizes are limited. Its use contributes to stable and consistent predictions, which are important in institutional analyses and policy-oriented decision-making. The Decision Tree Classifier was included due to its high level of interpretability. By representing decisions as a set of simple, hierarchical rules, decision trees allow educators and administrators to intuitively understand how recommendations are produced. This transparency supports trust and accountability, which are essential in educational applications of artificial intelligence. The Multilayer Perceptron Classifier introduces a neural network-based perspective capable of capturing more complex, non-linear patterns in educational data. While less directly interpretable, its inclusion enables the meta-model to learn from richer interactions among data characteristics, particularly in large or diverse datasets commonly found in learning analytics systems. The K-Nearest Neighbors Classifier was selected as an instance-based learning approach that makes recommendations based on similarity to previously observed cases. This aligns well with common educational reasoning practices, such as comparing learners or courses with similar profiles, and provides an intuitive complement to more model-driven approaches.

Together, these four classifiers ensure methodological diversity and enhance the robustness of the meta-model across different educational scenarios.

3.2. Evaluation metrics

To evaluate the performance of the meta-model, a set of complementary metrics was employed, each reflecting a different aspect of practical relevance in education. Accuracy was used as a general measure of overall correctness, providing an initial indication of how often the model produces correct recommendations. Precision and recall were included to address the asymmetric costs of errors in educational decision-making. For example, in identifying students at risk, false positives may lead to unnecessary interventions, while false negatives may result in missed support opportunities. The F1-score was therefore used as a balanced metric that integrates both precision and recall into a single measure. Cohen's kappa coefficient was applied to assess the level of agreement between predicted and actual outcomes beyond chance. This metric is particularly valuable in educational datasets that exhibit class imbalance, such as when only a small proportion of students are classified as at risk.

Finally, computational time was measured to account for practical implementation constraints. In many educational institutions, analytical tools must operate under limited computational resources or provide timely results to support decision-making processes. Including execution time as a metric ensures that the proposed approach remains feasible for real-world deployment.

3.3. Cross validation strategy

To ensure the robustness and generalizability of the meta-model, a cross-validation strategy was employed during the evaluation process. Cross-validation allows the model to be tested on multiple subsets of the data, reducing the risk that results are driven by specific data partitions or characteristics of a single training set. In this study, the available data were systematically divided into training and validation subsets across multiple iterations. In each iteration, the meta-model was trained on a portion of the data and evaluated on unseen data. This procedure provides a more reliable estimate of model performance and supports fair comparison among the different classification methods.

From an educational perspective, cross-validation strengthens the credibility of the findings by demonstrating that the recommendations are not limited to a single dataset or context. Instead, the approach simulates how the meta-model would perform when applied to new educational settings, institutions, or learner populations. This is particularly important for policy makers and educational leaders who require evidence that analytical tools are robust, transferable, and suitable for broader adoption.

Overall, the combination of diverse classifiers, education-relevant evaluation metrics, and cross-validation contributes to a methodological framework that supports trustworthy and evidence-based machine learning recommendations in education.

4. Results

The empirical development of the proposed meta-model was conducted using 15 openly available educational datasets. All datasets addressed classification tasks related to student performance, focusing on the categorization of students according to academic outcomes, such as achievement levels, course success, or risk of underperformance. This common focus ensured conceptual consistency across datasets and allowed meaningful comparison of algorithm performance within a shared educational objective.

The datasets varied in size, structure, and contextual background, reflecting the diversity typically encountered in educational research and practice. They included data derived from different educational settings and levels, such as secondary and higher education, and incorporated a range of student-related attributes, including academic records, assessment results, and engagement indicators. Despite these differences, all datasets were unified by their purpose: supporting data-informed understanding of student success.

All data sources used in this study were openly accessible, promoting transparency, reproducibility, and ethical use of educational data. The datasets were collected from well-established open repositories, including Data in Brief and Kaggle, which are widely used in educational data mining and learning analytics research. The use of open data supports broader comparability of results and enables future researchers to replicate and extend the findings presented in this study.

By restricting the experimental setting to classification problems related to student performance, the study provides a focused evaluation of the proposed meta-model within a highly relevant educational domain. This design choice ensures that the reported results are directly applicable to common educational use cases, such as identifying students at risk, evaluating learning outcomes, and supporting targeted interventions. At the same time, the diversity of datasets strengthens the robustness of the analysis and supports the generalizability of the observed performance patterns across different educational contexts.

The results of the meta-model evaluation reveal meaningful differences among the four classification approaches, highlighting important trade-offs between predictive performance, interpretability, and practical feasibility in educational contexts. Rather than identifying a single “best” model, the findings underline the value of context-aware algorithm selection, which is central to the proposed meta-model.

Table 2. Evaluation of meta-models

	accuracy	precision	recall	f1	kappa	time
Ridge Classifier	0.57	0.55	0.57	0.55	0.13	2.01
Decision Tree Classifier	0.56	0.56	0.56	0.55	0.16	27.19
MLP Classifier	0.63	0.41	0.63	0.50	0.00	51.89
KNeighbors Classifier	0.59	0.52	0.59	0.54	0.08	20.83

The Multilayer Perceptron (MLP) Classifier achieved the highest overall accuracy (0.63) and recall (0.63), indicating a strong ability to identify relevant cases across datasets. From an educational perspective, this suggests that more complex models may be effective in capturing broad patterns in educational data, particularly when the goal is to ensure that fewer relevant cases - such as students at risk - are overlooked. However, this advantage is accompanied by notably lower precision and an extremely low Cohen’s kappa value, indicating limited reliability beyond chance agreement.

Additionally, the MLP required the longest computational time. These findings highlight an important limitation: while complex models may appear attractive based on accuracy alone, their lack of transparency, stability, and efficiency may reduce their suitability for routine educational use or policy-level decision-making.

In contrast, the Ridge Classifier demonstrated balanced performance across all evaluation metrics. Although its accuracy was lower than that of the MLP, it achieved relatively stable precision, recall, and F1-score values, along with a reasonable kappa coefficient and the shortest computation time. This combination makes the Ridge Classifier particularly appealing for educational institutions seeking efficient, interpretable, and scalable solutions. Its consistent behavior supports use cases where transparency and reproducibility are prioritized over marginal gains in accuracy.

The Decision Tree Classifier showed comparable accuracy and F1-score to the Ridge Classifier but achieved the highest kappa value among all models. This suggests stronger agreement beyond chance and reinforces the suitability of decision trees for educational applications where interpretability and trust are critical. However, its significantly higher computational time indicates potential limitations for large-scale or real-time implementations.

The K-Nearest Neighbors (KNN) Classifier offered moderate performance across all metrics, reflecting its intuitive, similarity-based reasoning. While not the strongest performer in any single metric, its balanced profile and conceptual simplicity make it a viable option in smaller-scale educational settings or exploratory analyses.

Overall, these results reinforce the central premise of this study: algorithm selection in education should not be driven by accuracy alone. Metrics such as kappa and computational time provide crucial insights into reliability and feasibility, while interpretability remains a key requirement for ethical and responsible AI use in education.

5. Discussion

For educators and policy makers, the findings emphasize the importance of adopting recommendation frameworks—such as the proposed meta-model—that support evidence-based, transparent, and context-sensitive decisions. By aligning algorithmic choices with educational goals and institutional constraints, the meta-model contributes to more trustworthy and sustainable AI integration in education.

The findings of this study highlight the importance of moving beyond ad hoc and technically driven approaches to machine learning adoption in education. As educational institutions increasingly rely on data-informed decision-making, there is a growing need for frameworks that are not only effective but also understandable, transparent, and aligned with educational values. The proposed meta-model addresses this need by supporting more informed algorithm selection while reducing the cognitive and technical burden placed on educators and decision-makers.

From the perspective of educators, one of the main contributions of this work lies in its practical usability. Rather than requiring in-depth knowledge of machine learning techniques, the meta-model translates complex algorithmic considerations into meaningful recommendations based on observable characteristics of educational data and tasks. This allows educators and educational researchers to focus on pedagogical questions—such as identifying students in need of support or evaluating learning progress—without becoming entangled in technical implementation details. By providing explainable recommendations, the model also supports reflective practice, enabling educators to understand why certain analytical approaches may be more suitable in specific educational contexts.

For policy makers and institutional leaders, the proposed framework offers a valuable decision-support tool for guiding the strategic adoption of artificial intelligence in education. Policy decisions related to learning analytics platforms, digital assessment tools, or early warning systems often involve trade-offs between accuracy, transparency, cost, and ethical considerations. The meta-model contributes to more evidence-based policy design by making algorithm selection more systematic and justifiable. In particular, its emphasis on explainability aligns with emerging regulatory and ethical frameworks that call for accountability and human oversight in AI-supported educational systems.

Furthermore, the meta-model has implications for capacity building and institutional governance. By reducing reliance on trial-and-error experimentation, it can help institutions allocate resources more efficiently and promote consistent practices across educational programs. This is especially relevant in contexts where technical expertise is limited or unevenly distributed. The framework can also serve as a common reference point for dialogue between technical experts, educators, and administrators, fostering shared understanding and interdisciplinary collaboration. Overall, the discussion underscores that effective use of machine learning in education is not solely a technical challenge but a socio-educational one. By bridging algorithmic complexity and educational needs, the proposed meta-model supports more responsible, transparent, and sustainable integration of AI into educational practice and policy.

6. Conclusion

This study set out to support more informed and responsible use of machine learning in education by proposing a meta-model for recommending algorithms based on data and task characteristics. The findings provide several important insights for educators, institutional leaders, and policy makers who are increasingly engaged with data-driven educational innovation.

A key insight emerging from the results is that higher predictive accuracy alone does not necessarily indicate greater practical value in educational contexts. While more complex models demonstrated strong performance in terms of accuracy and recall, they often showed limitations in reliability, interpretability, and computational efficiency. In contrast, simpler and more transparent models achieved more balanced performance across evaluation metrics and offered advantages in terms of explainability and scalability. This reinforces the importance of aligning algorithm selection with educational goals, institutional capacities, and ethical considerations, rather than relying solely on technical performance indicators.

From a practical standpoint, the proposed meta-model offers actionable guidance for educators and educational researchers who may lack advanced technical expertise. By translating prior empirical evidence into understandable recommendations, the framework reduces reliance on trial-and-error experimentation and lowers barriers to entry for meaningful engagement with learning analytics and educational data mining. For policy makers, the meta-model supports evidence-based decision-making by providing a structured and transparent rationale for algorithm selection in institutional systems, early warning mechanisms, and digital learning platforms. Its explainable nature aligns well with current expectations for accountability and human oversight in AI-supported educational systems.

Despite these contributions, several limitations should be acknowledged. First, the study focused exclusively on classification tasks, which, while highly relevant to common educational problems such as student performance prediction and risk identification, do not capture the full range of analytical needs in education. Second, the meta-model was evaluated using a relatively limited number of datasets (15 educational datasets), which may constrain the generalizability of the findings across diverse educational contexts and data environments.

These limitations point to several promising directions for future research. Future studies could extend the meta-model to include regression, clustering, and sequence-based tasks, thereby broadening its applicability to additional educational use cases such as learning progression modeling and curriculum optimization. Expanding the number and diversity of datasets would further strengthen the robustness and transferability of recommendations. Future work may also integrate additional evaluation criteria, such as fairness, bias sensitivity, and long-term educational impact, to better support responsible AI governance in education.

In conclusion, this research demonstrates that meta-learning approaches can play a valuable role in bridging the gap between algorithmic complexity and educational practice. By focusing on explainability, practicality, and evidence-based reasoning, the proposed meta-model contributes to more trustworthy, efficient, and context-aware adoption of machine learning in education.

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