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Bridging ethics and performance in engineering education through predictive learning analytics

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ABSTRACT

This literature review examines the opportunities, implementation challenges, ethical implications, and emerging directions of predictive learning analytics (PLA) in engineering education. Using a structured review of the literature, the study synthesizes evidence from several publications with emphasis on studies examining risk prediction, personalized support, curricular improvement, interpretability, fairness, and intervention design. The review shows that PLA can improve early identification of at-risk students, support adaptive learning pathways, and inform data-driven refinements in engineering curricula; however, its impact depends on data quality, model transparency, institutional capacity, and the availability of timely human support. The analysis further indicates that the most consequential barriers are fragmented data ecosystems, the difficulty of translating predictions into effective interventions, and unresolved ethical concerns related to privacy, bias, consent, and student agency. The article contributes to educational research by offering an integrated synthesis that connects technical development with pedagogical evaluation and ethical governance in engineering education. It concludes by proposing that future PLA adoption should align predictive modeling with explainable artificial intelligence, learning-theory-informed intervention design, and institution-level implementation strategies. Publications were selected for relevance to PLA in engineering education and then synthesized narratively across opportunities, challenges, ethics, and future directions.

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1. INTRODUCTION

Engineering education stands as a cornerstone of technological advancement and economic competitiveness globally. However, it is also a field persistently challenged by high attrition rates, particularly in the transition from foundational to advanced engineering courses [1]. The traditional model of engineering education often operates on a reactive basis, identifying student difficulties only after poor performance on high-stakes assessments. This approach fails to address the complex, multifaceted nature of student learning and struggle in a timely manner. In response to these challenges, the field of learning analytics has emerged, defined as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [2]. A particularly potent subset of learning analytics is predictive learning analytics (PLA), which employs statistical and machine learning models on historical and current data to forecast future student outcomes, such as the likelihood of course failure, dropout, or academic success [3].

The application of PLA in engineering education is not merely an incremental improvement but a transformative opportunity. Engineering curricula are often sequential and cumulative, where failure in a prerequisite course can derail a student's entire academic trajectory. The ability to predict such outcomes early in a semester allows educators and institutions to intervene proactively, providing targeted support before it is too late [4]. Furthermore, the laboratory-intensive, project-based, and problem-solving-oriented nature of engineering generates rich, complex datasets beyond simple gradebooks, including data from learning management systems (LMS), code repositories, computer-aided design (CAD) software, and simulation tools. This data richness makes engineering education a particularly fertile ground for sophisticated PLA models. Predictive analytics using machine learning involves several systematic steps to transform raw data into actionable insights. The process begins with data collection from various sources, followed by data preprocessing to handle missing values, noise, and normalization, as shown in Figure 1. Feature selection and engineering enhance model relevance by identifying key predictors. Next, model selection and training use algorithms such as regression, decision trees, or neural networks to learn patterns from data. The trained model undergoes evaluation using metrics like accuracy to ensure reliability. Finally, the model is deployed for real-time predictions and continuously monitored for performance and retraining when necessary [4], [5].

Figure 1. Steps involved in performing predictive analytics using machine learning

The scholarly foundation for PLA in engineering education is built upon a convergence of research from educational data mining, computer science, and the learning sciences. Early work in this domain focused predominantly on identifying key predictors of student performance. Seminal studies demonstrated that simple, readily available data from university information systems, such as high school grade point average and standardized test scores, possessed significant predictive power for first-year engineering success [6]–[8] However, these demographic and pre-entry variables are static and offer little insight for ongoing intervention once a student is enrolled.

Subsequent research shifted towards leveraging dynamic, course-level data, primarily from LMS. Variables such as frequency of LMS access, time spent on content pages, assignment submission timeliness, and quiz performance have been widely used to build predictive models of final grades and dropout risk in engineering courses like programming, calculus, and introductory mechanics [9], [10]. For instance, previous study [11] successfully predicted student performance in a programming course using features extracted from version control systems, analyzing coding behavior patterns rather than just outcomes. Similarly, research in project-based engineering courses has explored using data from collaborative platforms to predict team performance and identify dysfunctional group dynamics [12].

The methodological evolution is also notable. While early models relied on traditional statistical techniques like logistic regression, recent studies have increasingly adopted more complex machine learning algorithms. Decision trees, random forests, support vector machines, and neural networks have been employed, often claiming superior accuracy [13], [14]. A systematic review highlighted that model performance varies considerably based on the context, chosen features, and specific prediction task [15]. Furthermore, a critical line of research has begun to question the sole focus on predictive accuracy, advocating for a greater emphasis on model interpretability and action ability. Previous study [16] have explored Explainable Artificial Intelligence (XAI) techniques in educational contexts, arguing that for a model to be useful for instructors, it must not only predict but also provide understandable reasons for its predictions.

Despite this growing body of literature, significant gaps remain. Many studies are confined to a single course or institution, limiting the generalizability of findings [17]. There is also a recognized "transfer problem" in learning analytics, where a model trained on one cohort of students may perform poorly on another without careful recalibration [18]. Moreover, the majority of research has focused on the technical construction of predictive models, with far less attention paid to the integration of these models into actual pedagogical practices or the study of their longitudinal impact on student retention and learning outcomes [19]. This review seeks to contextualize these related studies within the broader framework of opportunities, challenges, and ethics that define the responsible path forward for PLA in engineering education.

Within this context, a clearer research gap must be articulated. Although prior studies have demonstrated the feasibility of predicting academic risk, the literature remains fragmented across technical model-development papers, course-specific case studies, and ethics discussions. Fewer review-oriented works synthesize how PLA intersects with learning evaluation in engineering education—that is, how predictive indicators are translated into formative feedback, support decisions, curriculum redesign, and evidence of improved learning outcomes. Accordingly, this article addresses the gap by connecting prediction accuracy with pedagogical use, evaluative decision-making, and ethical responsibility in engineering programs. To strengthen methodological transparency, the review was organized as a structured narrative literature review. The analysis focused on publications addressing PLA applications, implementation barriers, ethical concerns, and future directions in engineering education.

This study adopts a structured narrative literature review approach. Publications were selected based on their direct relevance to PLA in engineering education, with emphasis on studies addressing early risk detection, personalized support, curricular improvement, model interpretability, fairness, ethics, and implementation. The synthesis was organized thematically to examine opportunities, challenges, ethical responsibilities, and future directions while keeping the discussion centered on educational decision-making rather than technical performance alone.

The primary objective of this review article is providing a comprehensive and critical examination of the application of PLA within engineering education. It moves beyond a simple technological narrative to explore the multifaceted interplay between data-driven opportunities, significant practical and technical challenges, and profound ethical considerations. The structure of this article is designed to first establish the current state of the field through an analysis of related studies, then to expansively discuss the promises and perils of PLA, and finally to reflect deeply on the ethical imperatives and future directions that must guide its responsible development and deployment. By synthesizing a broad body of literature, this review aims to serve as a foundational resource for educators, administrators, data scientists, and policymakers engaged in the complex task of preparing the next generation of engineers.

2. OPPORTUNITIES

The implementation of PLA in engineering education presents a multitude of compelling opportunities that can fundamentally enhance both student outcomes and institutional effectiveness. The most prominent of these is the capacity for early identification of students at risk of academic failure. In the demanding, sequential curriculum of engineering, a failure in a core course can have cascading effects, delaying graduation or causing students to leave the discipline entirely. PLA models can analyze patterns of engagement and performance within the first few weeks of a semester—such as declining LMS activity, missed assignments, or low scores on initial assessments—to flag students who may be struggling [20]. This enables a shift from reactive support, offered after a student has failed a midterm, to proactive intervention, where academic advisors or instructors can reach out with resources, tutoring, or counseling at the first sign of trouble [4]. This timely support is crucial for retaining students, particularly those from underrepresented groups who may face additional barriers in engineering [21].

Beyond risk identification, PLA holds immense promise for the personalization of learning. The "one-size-fits-all" model of lecture-based instruction is increasingly seen as inadequate for addressing the diverse backgrounds and learning preferences of engineering students, as shown in Figure 2. The one-size-fits-all education model delivers uniform instruction to all students, assuming similar learning needs and paces. It emphasizes standardized curricula, fixed teaching methods, and common assessments, often overlooking individual differences in learning styles, abilities, and interests leading to disengagement and limited personalization in achieving optimal educational outcomes. Analytics can power adaptive learning systems that recommend specific learning materials, practice problems, or alternative pedagogical pathways based on a student's unique profile and performance [22], [23]. For example, a student struggling with conceptual understanding in a thermodynamics course could be automatically directed to interactive simulations, while a student struggling with mathematical derivations could receive targeted problem sets [24]. This moves engineering education towards a more mastery-based model, where students progress upon demonstrating competence rather than simply spending time in a classroom.

Furthermore, PLA provides an unprecedented opportunity for evidence-based curriculum and pedagogical refinement. By analyzing data aggregated across multiple cohorts, educators and program administrators can identify specific topics, assignments, or learning activities that consistently correlate with student difficulty [25]. For instance, if analytics reveal that a significant portion of students consistently fails a particular assignment linked to a fundamental concept like free-body diagrams in statics, it signals a need to re-examine the teaching methods or instructional materials for that concept [26]. This data-driven feedback loop allows for continuous improvement of course design and teaching strategies, moving beyond anecdotal evidence to inform decisions about curriculum sequencing, the effectiveness of new teaching methodologies like flipped classrooms or project-based learning, and resource allocation for teaching assistants and lab equipment [27]. Ultimately, PLA can transform the role of the engineering educator from a sole knowledge disseminator to a designer of learning experiences, informed by rich, empirical data on student learning processes. Table 1 shows the opportunities of PLA in engineering education. Although the opportunities of PLA are often presented conceptually, the literature also reports empirical benefits when analytics are paired with timely instructional action. Early-alert systems and personalized feedback studies have associated PLA-informed interventions with improved course engagement, better assignment completion, stronger persistence, and, in some settings, higher pass rates [4], [20], [24]. At the same time, the evidence suggests that positive effects are uneven rather than automatic: gains depend on the timing of alerts, the relevance of support provided, the quality of the underlying data, and the instructional context in which interventions are enacted. This indicates that PLA should be evaluated not only by predictive accuracy but also by whether it measurably improves learning processes and outcomes within specific engineering courses and programs.

Figure 2. Key characteristics of one-size-fits-all education

Table 1. Opportunities of PLA in engineering education

Aspect	Description	Potential impact	Application
Early identification of at-risk students	PLA can detect students likely to fail early by analyzing LMS activity, missed assignments, or poor early assessments.	Enables proactive interventions instead of reactive ones, improving retention and success rates.	Advisors reach out to struggling students with tutoring or counseling within the first few weeks.
Personalized learning pathways	PLA supports adaptive learning systems that tailor educational content to each student's needs.	Enhances learning engagement and comprehension by accommodating diverse learning styles.	A thermodynamics student struggling conceptually is directed to simulations; another gets targeted math exercises.
Data-driven curriculum refinement	Analytics highlight patterns of student difficulty across topics and cohorts.	Facilitates evidence-based improvement of teaching methods and course design.	Reassessing teaching methods when analytics show persistent failure in topics like free-body diagrams.
Promotion of mastery-based learning	Students' progress based on demonstrated competence rather than time spent.	Improves deep understanding and long-term retention of engineering concepts.	Adaptive assessment systems unlock new modules only after mastery of prior content.
Transformation of educator roles	Educators evolve from content deliverers to data-informed learning designers.	Promotes reflective teaching practices and continual pedagogical improvement.	Instructors use analytics dashboards to refine flipped-classroom strategies.

3. CHALLENGES

Despite its significant potential, the effective implementation of PLA in engineering education is fraught with substantial challenges. Among these, the most consequential are: i) fragmented and low-quality data infrastructures, because weak data undermine every subsequent stage of analysis; ii) the intervention gap between prediction and meaningful pedagogical action; and iii) limited model interpretability, which constrains educator trust and practical use. Other challenges, including sustainability, governance, and staff capacity, intensify these core barriers and often determine whether PLA initiatives move beyond pilot projects. Engineering learning environments are heterogeneous, generating data from disparate sources including institutional SIS, LMS (e.g., Canvas, Moodle), specialized software (e.g., MATLAB, SolidWorks), simulation platforms, and physical lab equipment [28]. Integrating these siloed data into a coherent, clean, and time-synchronized dataset for analysis is a non-trivial task that requires significant institutional investment in data infrastructure and governance [29]. Inconsistent data formats, missing values, and the logistical complexities of creating a unified student record pose major obstacles to building reliable and comprehensive predictive models.

A second, critical challenge lies in the development of models that are not only accurate but also transparent, interpretable, and actionable for educators. While complex machine learning models like deep neural networks may achieve high predictive accuracy, they often operate as "black boxes," providing little insight into the reasoning behind their predictions [30], [31]. An instructor receiving an alert that a student has a 90% risk of failure is left with a critical question: "Why?" Without interpretable explanations—such as "the student has not accessed the last three lecture videos and scored below 50% on the first two quizzes"—the instructor lacks the contextual knowledge to design an effective, personalized intervention [16]. The pursuit of interpretability may sometimes come at the cost of slight reductions in accuracy, necessitating a trade-off that prioritizes practical utility over purely statistical performance [32].

Moreover, the mere identification of at-risk students is insufficient; the "last mile" problem of linking predictions to effective interventions remains a significant challenge. Simply notifying a student that they are predicted to fail can be demotivating or induce anxiety if not handled with care and coupled with supportive, actionable guidance [33]. Institutions must develop robust intervention protocols that define who acts on an alert, how they communicate with the student, and what resources are made available [34]. This requires training for faculty and advisors, a clear understanding of student support ecosystems, and a cultural shift towards a proactive support model. Finally, there is the challenge of sustainability and scalability. Many PLA initiatives begin as small-scale research projects; transitioning them into sustainable, institution-wide practices requires ongoing technical maintenance, dedicated personnel, and a long-term strategic commitment from leadership, all of which can be difficult to secure in resource-constrained academic environments [35]. Table 2 shows the challenges of PLA in engineering education. A critical perspective, these challenges are not equally weighted. Data integration and intervention design are arguably the highest-priority concerns because even highly accurate models deliver limited educational value when institutions cannot assemble reliable data or convert risk signals into timely support. Similarly, interpretability is not merely a technical preference; it is a condition for accountability, trust, and actionability in educational settings. Therefore, the central implementation question is not whether PLA can predict outcomes, but whether institutions can build a pedagogically credible system in which data pipelines, human decision-making, and student support are coherently aligned.

Table 2. Challenges of PLA in engineering education

Aspect	Description	Impact/Consequence	Possible mitigation strategies
Data integration and quality	Data originates from multiple, inconsistent sources like LMS, SIS, and lab tools.	Leads to unreliable predictions and fragmented analysis.	Develop institutional data governance frameworks and standardized data pipelines.
Model interpretability and transparency	Complex models (e.g., neural networks) lack explainability for instructors.	Educators cannot understand why a student is at risk, limiting actionability.	Use interpretable machine learning (ML) models and generate human-readable explanations.
Last-mile problem (Intervention gap)	Predicting risk is not enough—actionable, empathetic intervention protocols are often missing.	Students may feel demotivated or anxious when labeled “at-risk.”	Combine predictions with supportive feedback and advisor training.
Institutional capacity and sustainability	Implementing and maintaining PLA systems require long-term resources and leadership commitment.	Initiatives may fail after pilot stages due to lack of funding or expertise.	Secure institutional support and integrate PLA into strategic academic planning.
Accuracy vs. utility trade-off	Highly accurate models may sacrifice interpretability.	Limits practical adoption and educator trust.	Balance predictive accuracy with human interpretability and usefulness.

4. ETHICAL REFLECTIONS

The power of PLA is inextricably linked to profound ethical implications that demand careful and continuous reflection. Foremost among these are concerns regarding student privacy, data ownership, and the nature of consent. The extensive data collection required for PLA—tracking every click, login, and submission—creates a detailed digital footprint of a student's life, raising questions about surveillance and the "panopticon" effect, where students may alter their natural behavior knowing they are being monitored [36]. While institutions have a legitimate educational interest in using data to support students, the boundaries of this interest must be clearly defined. The concept of informed consent is particularly complex in an educational context, where power dynamics between students and institutions can make it difficult for consent to be truly voluntary [37]. Students may feel pressured to opt-in to data collection for fear of missing out on support or being perceived negatively by instructors.

Another paramount ethical concern is algorithmic bias and fairness. Predictive models are not objective; they learn patterns from historical data, which often reflect existing societal and educational inequities. If past data shows that certain demographic groups have historically underperformed in engineering courses, a model trained on this data may perpetuate or even amplify these biases by systematically assigning higher risk scores to students from those groups, creating a self-fulfilling prophecy [38], [39]. This poses a grave threat to efforts to diversify the engineering workforce. Rigorous auditing for fairness and bias is therefore not an optional add-on but an essential component of responsible PLA development [40]. Techniques must be employed to detect and mitigate bias, ensuring that models do not disproportionately disadvantage students based on protected characteristics such as race, gender, or socioeconomic status.

Furthermore, there is an ethical risk of reducing students to their data points, potentially undermining their agency and autonomy. An over-reliance on algorithmic predictions may lead to a form of educational determinism, where a student is labeled as "at-risk" and consequently channeled into a narrow, predefined support path, limiting their opportunities for self-directed recovery and growth [41]. It is crucial to frame PLA as a tool to augment, not replace, human judgment and meaningful student-instructor relationships. The goal should be to create a supportive, rather than a surveillance, infrastructure. Finally, issues of data governance, security, and transparency are critical. Institutions must have clear policies on who has access to student data, for what purposes, how long it is retained, and how it is protected from breaches [42]. A commitment to algorithmic transparency, where the logic of models is explainable to stakeholders, is a key pillar of building trust and ensuring the ethical deployment of PLA in engineering education. Table 3 shows the ethical reflections on PLA in engineering education. In practice, this requires a human-in-the-loop approach in which instructors and advisors interpret analytics outputs alongside contextual knowledge, student voice, and institutional support obligations.

Table 3. Ethical reflections on PLA in engineering education

Ethical dimension	Description	Risk/Concern	Ethical guideline
Privacy and consent	PLA involves extensive data collection from student interactions.	Risk of surveillance culture and coerced consent.	Ensure transparent consent processes and data minimization policies.
Algorithmic bias and fairness	Models can inherit historical inequities in educational data.	Disadvantaging marginalized groups, reinforcing systemic bias.	Conduct regular bias audits and apply fairness-aware ML techniques.
Student autonomy and agency	Over-reliance on predictions may label and limit students.	Risk of educational determinism and loss of self-efficacy.	Use PLA as supportive tools, not as deterministic evaluators; preserve human oversight.
Data governance and security	Managing who accesses, stores, and retains sensitive data.	Data breaches or misuse of personal information.	Enforce strict governance, encryption, and data access policies.
Transparency and trust	Students and educators must understand how analytics influence decisions.	Lack of transparency can erode confidence and acceptance.	Implement algorithmic explainability and stakeholder communication frameworks.

5. FUTURE TRENDS

The field of PLA for engineering education is poised to evolve rapidly, driven by advancements in technology and a growing sophistication in pedagogical understanding. Several key trends are likely to shape its future trajectory. A significant move will be towards the integration of multimodal data streams to create more holistic and nuanced student models. Future PLA systems will move beyond LMS clicks and grades to incorporate data from a wider array of sources, such as natural language processing (NLP) of discussion forum posts and written reports, analysis of code complexity and development processes, affective computing to detect engagement and frustration through facial expression or keystroke dynamics in lab settings, and even data from wearable sensors in hands-on, practical laboratories [43], [44]. This multimodal approach promises a richer understanding of the cognitive, behavioral, and affective dimensions of engineering learning.

Concurrently, there will be a strong push towards the development and standardization of XAI in education. The research community recognizes that the "black box" problem is a major barrier to adoption and trust [30]. Future work will focus on creating models that are intrinsically interpretable or developing sophisticated post-hoc explanation interfaces that can provide instructors with clear, contextual, and actionable insights, such as “Student A is struggling specifically with concepts X and Y, as evidenced by their performance on quizzes 3 and 4 and their lack of engagement with the corresponding simulation module” [16], [45]. This will bridge the gap between prediction and effective pedagogical action.

Another emerging trend is the focus on predicting and fostering competencies beyond academic grades, such as design thinking, creativity, collaboration, and professional skills. Engineering accreditation bodies increasingly emphasize these outcomes [46]. PLA models will be developed to analyze data from project portfolios, peer assessments, and collaborative tools to provide feedback on a student's development of these crucial, yet difficult-to-measure, competencies [47]. Finally, we can anticipate a greater emphasis on interoperability standards (e.g., using Caliper Analytics) to simplify data integration and the exploration of federated learning techniques, which allow for model training across institutions without sharing raw student data, thereby addressing some privacy and data sovereignty concerns [48]–[50]. These trends, collectively, point towards a future where PLA becomes a more integrated, intelligent, and ethically-aware partner in the education of engineers.

These technological developments will be most valuable when they are anchored in contemporary learning theories. For example, adaptive PLA systems align with mastery learning by identifying gaps before student’s progress, while dashboard-based feedback can support self-regulated learning by helping students monitor effort, strategies, and progress over time. In collaborative engineering environments, analytics-informed feedback can also be interpreted through social constructivist perspectives, particularly when it is used to strengthen peer interaction, project-based learning, and reflective practice. From an implementation standpoint, institutions should begin with clearly defined educational objectives, pilot PLA in high-risk gateway courses, establish transparent governance and consent procedures, train instructors to interpret analytics outputs, and evaluate success using both predictive metrics and learning-outcome indicators.

6. CONCLUSION

This review shows that PLA has value in engineering education not simply because it can predict academic outcomes, but because it can support earlier, more targeted, and more evidence-informed educational decisions. Across the literature, the strongest opportunities relate to early risk detection, personalization, and curriculum refinement, whereas the most significant barriers involve data fragmentation, limited interpretability, intervention design, and ethical governance. The central contribution of this article to educational research is its integrated synthesis of these technical, pedagogical, and ethical dimensions within the specific context of engineering education, where sequential curricula and high-stakes progression make timely support especially important. The review also clarifies that learning analytics should be understood as part of learning evaluation: predictive signals become educationally meaningful only when they inform formative feedback, support strategies, and curriculum-level improvement. Future research should therefore move beyond model-comparison studies toward multi-institutional evaluations, longitudinal analyses of intervention effectiveness, fairness audits across student groups, and theory-informed implementation frameworks that examine how PLA influences learning, retention, and student agency over time. This revision therefore clarifies that responsible PLA adoption should be judged not only by prediction metrics, but also by the quality of feedback, equity safeguards, and demonstrable improvement in student learning and retention.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
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P : **P**roject administration
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CONFLICT OF INTEREST STATEMENT

Authors declare no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this paper.

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