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PREDICTING STUDENT MOTIVATION AND ENGAGEMENT THROUGH MACHINE LEARNING MODELS

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Abstract:
Student motivation and engagement are pivotal yet latent constructs that benefit from timely, data-driven prediction to inform proactive support in higher education. This paper presents a concise synthesis of machine learning approaches for predicting multi-dimensional engagement (behavioral, emotional, cognitive) and academic motivation (intrinsic, extrinsic), bridging theory with deployable practice. We outline common data sources—learning management system (LMS) interaction logs, assessment trajectories, attendance and academic records, and psychometric instruments—and emphasize feature engineering for temporal dynamics, interaction patterns, effort proxies, and context transfer across courses. The modeling landscape spans interpretable classifiers (logistic regression, decision trees, random forests, gradient boosting), kernel methods (support vector machines), and deep learning architectures for sequential signals (RNN/LSTM, temporal CNN, transformers), with growing interest in multimodal fusion and representation learning. Evidence indicates that temporal and interaction features substantially improve early-warning performance, while generalization benefits from course-agnostic features, calibration, and domain adaptation. It is believed that this paper will help future researchers to gain insight about the said domain.

Keywords: Student Engagement; Academic Motivation; Educational Data Mining; Machine Learning in Education; Learning Analytics; Predictive Modeling; Higher Education; Student Performance; Adaptive Learning; Early Warning Systems

1. INTRODUCTION

Student engagement and motivation are widely recognized as pivotal factors in higher education learning outcomes. Engagement – broadly defined as students' active involvement and participation in learning activities – has been linked to better academic performance, retention, and overall student success. Conversely, low engagement is often an early warning sign for academic difficulties or dropout. Student motivation, referring to the drive or desire to learn, underpins engagement; motivated students are more likely to invest effort and persist in the face of challenges [13][14]. However, *student engagement* is a complex, multifaceted construct subject to diverse interpretations. It encompasses behavioral aspects (e.g. participation, time on task), emotional responses (interest or enthusiasm), and cognitive investment in learning. *Student motivation* likewise includes multiple dimensions – commonly distinguished as intrinsic motivation (learning for inherent satisfaction), extrinsic motivation (driven by external rewards or outcomes), and *amotivation* (lack of motivation). Understanding and measuring these latent constructs pose significant challenges in educational research [15][16].
Recent shifts toward online and blended learning have further heightened the importance of monitoring engagement and motivation. During emergency remote teaching, for example, institutions observed varied student engagement patterns, prompting calls for better analytical insight into student involvement [17][18][19]. Traditional methods (such as self-report surveys or manual observation) to gauge engagement/motivation can be limited in accuracy and scalability. In this context, artificial intelligence and data analytics have emerged as valuable tools in higher education [20]. In particular, *machine learning (ML) models* can analyze the vast data generated by learning management systems and other platforms to *predict students' degree of engagement and motivation*. By identifying disengaged or demotivated students early, educators can intervene with targeted support before minor issues escalate into major problems. Such predictive insights enable a proactive approach to student success, aligning with the vision of learning analytics to inform timely, personalized pedagogical decisions [21][22][23].

Machine learning approaches have already shown considerable promise in this domain. Researchers have reported accurate classification of students' engagement levels using behavioral data, and strong correlations between model-predicted engagement and academic outcomes (e.g. course assessment scores) [24]. Models can effectively distinguish engaged vs. disengaged students, allowing instructors to focus attention on those most in need of intervention. A recent systematic review noted a surge in studies applying ML to predict student performance and engagement, underscoring the growing interest and confidence in these techniques. At the same time, challenges remain regarding data quality, generalizability, and the interpretability of complex ML models in educational contexts. This research work addresses both the theoretical underpinnings of student motivation and engagement and the practical application of ML models to predict them in higher education, with an emphasis on computer science and engineering education contexts (though the concepts generalize across disciplines) [25][26].

2. THEORETICAL FOUNDATIONS OF STUDENT ENGAGEMENT AND MOTIVATION

2.1 Student Engagement in Higher Education

Student engagement refers to the degree of attention, interest, curiosity, and involvement that students exhibit in the learning process. It is now understood as a *multidimensional construct* encompassing behavioral, emotional, and cognitive components. *Behavioral engagement* involves students' participation in academic activities and effort expended (e.g. attending classes, turning in assignments, contributing to discussions) [27][28]. *Emotional engagement* refers to affective responses to learning – such as interest, enjoyment, or a sense of belonging – and attitudes towards school or subject matter. *Cognitive engagement* denotes the investment in learning and willingness to exert mental effort to comprehend complex ideas or master skills. These facets often overlap and interact. Figure 1 depicts the relationship among the three core dimensions of engagement, which together contribute to a student's overall engagement level [29][30].

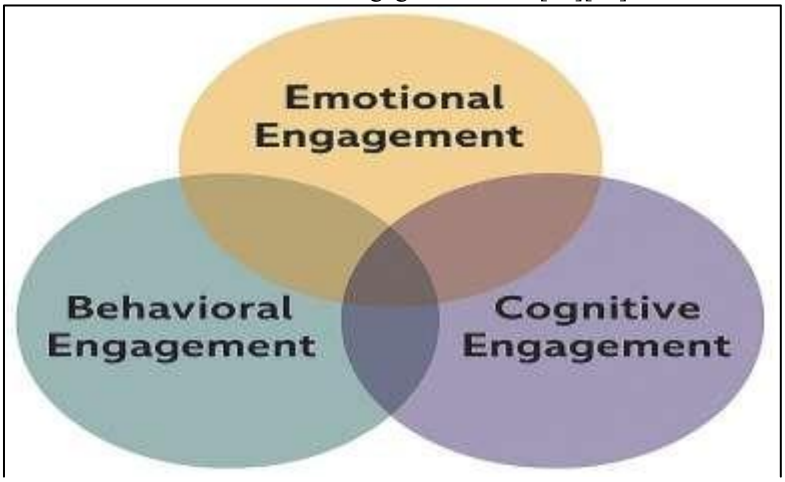

Figure 1: Key dimensions of student engagement and their overlap.

High levels of engagement are generally associated with positive educational outcomes. Engaged students tend to spend more time on task, persist through challenges, and use deeper learning strategies, leading to better understanding and performance. Empirical studies have shown that measures of engagement (such as time spent in coursework or interactive participation) correlate with higher course grades and lower likelihood of dropping out. For example, a recent study found that *highly engaged students achieved better assessment results than those with lower engagement* [31][32]. Conversely, low engagement often manifests as poor attendance, minimal assignment completion, or superficial interaction – factors that are strong predictors of academic difficulties and attrition. Indeed, lack of student engagement has been identified as an antecedent to course failure and student dropout in online and face-to-face settings. Early signs of disengagement (e.g. prolonged inactivity in an online course) can thus serve as crucial warning signals for instructors [33][34].

Importantly, student engagement is context-dependent and can fluctuate over time. Environmental factors such as course design, teaching methods, and peer interaction influence how students engage. For instance, collaborative and interactive learning activities can foster greater behavioral and emotional engagement than passive lecture formats. During the COVID-19 pandemic, sudden shifts to online learning highlighted how *lack of interaction with instructors and peers can undermine engagement*, leading to reduced motivation and increased withdrawals [35][36][37]. Researchers emphasize that engagement is not solely an individual student trait but also an outcome of the learning environment and teaching practices. According to recent frameworks, engagement can be viewed along a continuum from the *person-oriented perspective* (engagement arising from individual student's disposition) to a *context-oriented perspective* (engagement as a product of the learning context over time). This perspective reminds us that improving student engagement often requires both supporting students' skills and motivation and creating more engaging learning environments [38].

From a theoretical standpoint, student engagement has been called an "organizing framework" that ties together diverse influences on learning. It is both a mediator and an outcome: engagement mediates between student characteristics (or interventions) and learning results, and it is itself an outcome that educators seek to improve.

This central role of engagement in learning has made it a focal point for educational interventions and for predictive modeling, as discussed in later sections. Figure 2 illustrates the commonly observed positive correlation between student engagement and academic performance, highlighting why engagement is such a critical target for prediction and improvement efforts. This scatter plot (with a fitted trend line) shows a hypothetical positive correlation between students' engagement level (e.g. percentage of course activities completed) and their final course grade. Consistent with empirical research, more engaged students tend to achieve higher academic performance. Early identification of low-engaged students (lower left area) can prompt interventions to improve their outcomes [39][40][41][42].

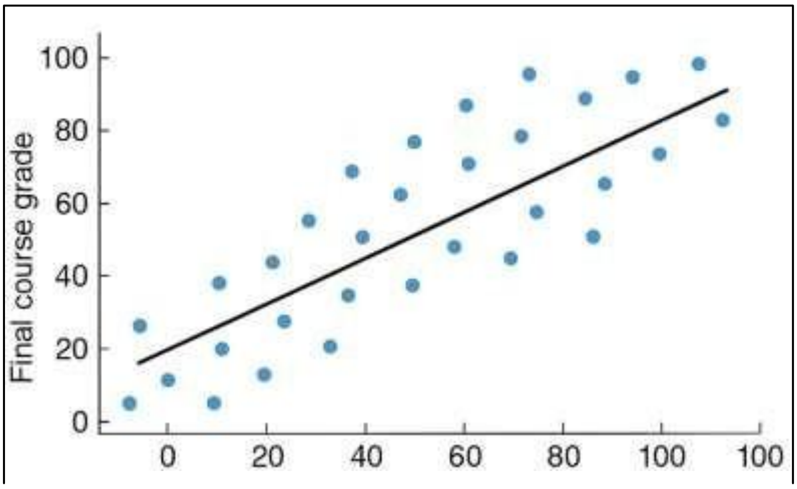

Figure 2: Relationship between engagement and academic performance.

2.2 Student Motivation in Higher Education

Student motivation broadly refers to the internal processes that initiate, sustain, and direct learning activities. In higher education, motivation influences whether students *want* to learn and how much effort and persistence they will dedicate to their studies. Educational psychologists distinguish between *intrinsic motivation* – engaging in learning out of genuine interest or enjoyment – and *extrinsic motivation* – engagement driven by external rewards or requirements (such as grades, credits, or praise) [43][44]. A student with high intrinsic motivation in a computer science course, for example, might spend extra hours experimenting with code out of curiosity, whereas an extrinsically motivated student might complete exercises primarily to earn a good grade. Some students may also experience *amotivation*, a state of lacking intent or incentive to learn, often accompanied by feelings that tasks are irrelevant or beyond one's control [45].

Academic motivation is grounded in several theoretical frameworks. One influential view is the *Self-Determination Theory (SDT)*, which posits that students are more intrinsically motivated when their basic psychological needs for autonomy, competence, and relatedness are satisfied. In a supportive learning environment where students feel a sense of control (autonomy), feel capable of mastering material (competence), and feel connected to others (relatedness), they are likely to develop stronger intrinsic motivation to engage in learning tasks [46][47]. Conversely, environments that undermine these needs (e.g. highly controlling instruction, excessive fear of failure, or social isolation) can diminish intrinsic motivation and lead to more superficial engagement. Other relevant constructs include self-efficacy (belief in one's capabilities to learn or perform) and goal orientation (whether a student is focused on mastering content versus just performing well or avoiding failure). These factors can modulate motivation levels and the quality of engagement. For instance, a student with high self-efficacy and a mastery goal orientation is likely to exhibit resilient, deep engagement in learning, even when faced with challenges [48].

Understanding what drives student motivation is crucial because motivation *energizes and directs engagement*. A motivated student is more likely to actively participate, persist longer, and employ effective learning strategies [49]. As one study highlighted, *understanding the drivers of academic motivation is essential for developing effective educational strategies*. Research has shown clear links between motivation and academic outcomes: students with higher intrinsic motivation often achieve better learning outcomes and report greater satisfaction, whereas students motivated purely by external factors may disengage once those factors are removed. Furthermore, motivation and engagement are deeply intertwined – motivation can be seen as a precursor to engagement (students must *want* to engage), and conversely, engaging successfully in learning can reinforce motivation (through experiences of enjoyment or accomplishment) [50][51].

In the context of higher education, especially in computing and engineering disciplines, maintaining student motivation can be challenging. Coursework is often rigorous and abstract, which may dampen the enthusiasm of students who do not immediately see the relevance or who encounter repeated failures. Educators thus strive to create motivating conditions: for example, relating course material to real-world applications (to increase perceived value), providing timely feedback and achievable challenges (to build competence), and fostering a supportive community (to satisfy relatedness). The rise of technology-mediated learning has introduced new opportunities and challenges for motivation. On one hand, gamification elements and interactive simulations can boost motivation by making learning more engaging. On the other hand, the relative anonymity and autonomy of online learning require students to be more self-motivated, which not all learners are prepared for. These considerations underscore why predicting and supporting motivation is as important as addressing engagement in modern educational settings [52][53].

Researchers have begun applying machine learning to understand and predict student motivation. Notably, because motivation is a latent psychological trait, direct measurement is often done via surveys or psychometric scales (e.g. rating one's interest or effort). Recent work has explored whether *other data sources can serve as proxies for motivation* – for example, analyzing students' behavioral patterns or personal traits. A novel study by Apampa *et al.* [3] leveraged **personality traits** as predictors of academic motivation. By collecting students' Big Five personality profiles, they trained ML models to predict levels of intrinsic motivation, extrinsic motivation, and amotivation. Interestingly, they found that certain personality factors (like conscientiousness and openness) were significant predictors of higher motivation, whereas neuroticism correlated with amotivation. Such findings align with intuition – students who are organized and open to experience tend to be more self-driven learners – and demonstrate how psychological features can be incorporated into predictive models [54][55]. While this line of research is still emerging, it holds promise for identifying students who may be at risk of low motivation (for instance, those whose personality or prior feedback suggests they might feel less competent or autonomous in a given course).

2.3 Linking Motivation and Engagement

Motivation and engagement are distinct but deeply connected constructs in the learning process. Motivation can be viewed as a *leading indicator* or underlying cause of engagement: a student who is highly motivated (particularly intrinsically) is far more likely to exhibit strong engagement behaviors [56]. Conversely, patterns of engagement can affect motivation – for example, a student who engages deeply and succeeds may become more motivated through increased confidence and interest, whereas chronic disengagement and poor performance can erode motivation. The dynamic interplay between these factors is depicted in Figure 3, which provides a conceptual model: personal factors feed into motivation, which in turn drives engagement behaviors, leading to academic outcomes; meanwhile, the learning environment (instructional context) also directly influences engagement [57].

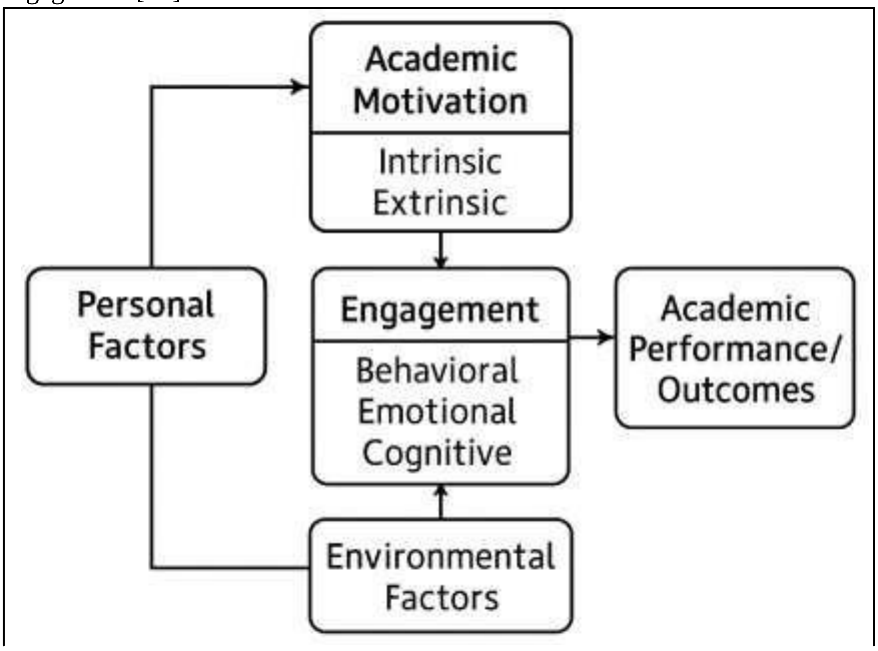

Figure 3: Relationship between student motivation and engagement in context.

Theoretical frameworks support this linkage. As noted, Self-Determination Theory suggests that when students feel autonomous, competent, and related (all of which bolster intrinsic motivation), they are more likely to engage wholeheartedly in learning tasks. In practical terms, a student who finds a subject personally interesting and valuable (intrinsic motivation) will typically pay closer attention, put forth more effort, and persist longer – classic manifestations of engagement [58]. Empirical research affirms this connection. For example, students who report higher motivation often show greater time spent on learning tasks and more active participation in class. In one longitudinal study, motivation at the start of a course predicted subsequent engagement patterns, which then predicted final grades. This suggests a causal chain: motivation → engagement → performance, although the relationships are reciprocally reinforcing rather than strictly one-way [59].

On the other hand, engagement experiences can loop back to influence motivation. When students engage and see progress or enjoy the learning process, it can enhance their self-efficacy and interest, fueling further motivation (a positive feedback cycle) [60]. Conversely, if students are unengaged and fall behind, they may feel less competent or autonomous, which can diminish their motivation to try – a negative feedback cycle. Educators thus face a critical task: breaking negative loops and fostering positive ones. Effective teaching strategies often target both motivation and engagement simultaneously. For instance, introducing real-world projects in a computing course can increase *situational interest* (boosting motivation) and also require active involvement (increasing engagement), ideally leading to a virtuous cycle of deeper learning [61].

Because of this intertwining, it can sometimes be hard to disentangle whether an intervention should be labeled as "motivational" or "engagement-focused" – most successful educational interventions address both. For example, providing students with choices in assignments can increase their intrinsic motivation (by supporting autonomy) and also lead to greater engagement in doing the chosen work. Similarly, timely and constructive feedback can bolster a student's motivation (by affirming competence and guiding improvement) and concurrently encourage sustained engagement with the material [62][63][64].

This synergy is reflected in data-driven educational research as well. Features indicative of engagement (like frequency of forum posts or quiz attempts) are often correlated with underlying motivational states. Modern learning analytics and ML models sometimes use engagement behaviors as *proxies* for motivation, given that motivation itself is not directly observable. However, researchers are also exploring direct modeling of motivation. The aforementioned study by Apampa *et al.* [3] combined personality and motivation surveys to train models that predict motivational orientations. Interestingly, by predicting who is likely to be intrinsically or extrinsically motivated, one can indirectly anticipate how those students might engage; for instance, extrinsically motivated students might engage primarily when grades are at stake, whereas intrinsically motivated ones may engage more consistently. In practice, a comprehensive predictive system might include both motivation and engagement indicators to get a full picture of student learning health [65][66].

3. Data Sources and Feature Engineering for Prediction

Machine learning models are only as good as the data fed into them. In the context of predicting student motivation and engagement, a rich array of data sources can be utilized. Key data types include students' online learning interaction logs, academic records, demographic information, and even psychological measures [67][68]. This section discusses common **features and indicators** extracted from these sources, and how they serve as proxies for engagement or motivation in predictive modeling. **Table 1** provides an overview of major feature categories frequently used in the literature, along with their prevalence in recent studies.

3.1 Behavioral and Academic Data

By far the most widely used features for predicting engagement are *behavioral indicators from Learning Management Systems (LMS)* and other educational platforms. These digital trace data capture students' day-to-day interactions with course materials and activities. In recent years, *over 90% of studies* on engagement prediction have leveraged LMS log file data [69][70]. Such behavioral features include: number of logins, frequency of content views, time spent on various pages or resources, number of forum posts or comments made, assignment submission timestamps, quiz attempt counts, video watch duration, and so on. These metrics reflect the quantity and pattern of a student's participation, and thus serve as observable signs of engagement level. For example, a student who consistently logs in daily, spends significant time reading course content, and participates in discussion forums is likely more engaged than a student who rarely logs in and skims or skips content [71].

Academic performance data are another important source. *Assessment results and grades* (e.g. quiz scores, assignment grades, GPA) are sometimes used as features to predict engagement or as related targets to co-predict. About 41.8% of studies incorporate academic performance variables (such as prior or mid-term scores) as inputs for predicting engagement or success [72]. The rationale is that performance and engagement are linked; past grades can contextualize a student's engagement behavior (e.g. a high-performing student may disengage if bored or already comfortable, whereas a low-performing student may disengage due to frustration). In some cases, academic scores are even used to derive engagement labels – for instance, defining *"engaged" students as those performing above a certain threshold* and training classifiers to predict that label. However, more often performance is a parallel outcome predicted alongside engagement (since ultimately educators care about both). It is worth noting that *academic background* attributes (like previous coursework, high school grades, etc.) have seen more limited use – only about 11.4% of studies utilize such data, perhaps due to availability or a focus on within-course behaviors [73][74].

Other behavioral data beyond the LMS can also be relevant. In traditional classrooms, one might include attendance records, participation in labs or group projects, and even co-curricular involvement. Some studies have begun to use **sensor or clicker data** from physical classrooms to gauge attention and participation, though these are less common [75]. A notable domain-specific example is in medical education: El-Beshbishi et al. [2] analyzed student engagement in a medical course by tracking interactions with course materials (frequency of viewing content, completing activities) in the LMS, alongside their assessment scores. They then applied nine ML algorithms to classify students' engagement level [76][77]. Such approaches highlight that behavioral features can span both online and offline (or hybrid) environments, capturing how students allocate time and effort. In Benabbes *et al.* [4], study of an e-learning environment, the authors considered a variety of log-based features – for instance, *the total number of forum posts and the total time spent on the platform* were used to model engagement levels [78]. These features intuitively represent how actively a learner is involved in course communications and materials. Figure 4 illustrates how these student data sources flow into feature extraction in a typical pipeline. ***Data sources*** (student information and interactions) are collected from systems such as the LMS, academic records, and surveys. Relevant features are extracted and preprocessed (e.g. counts of clicks, time spent, quiz scores, personality trait scores). A *machine learning model* (trained on historical data) then analyzes these features to predict a student's *engagement level or motivation state*. The predictions can trigger *interventions or feedback*, allowing instructors or systems to support students (e.g. contacting disengaged students or providing motivational resources).

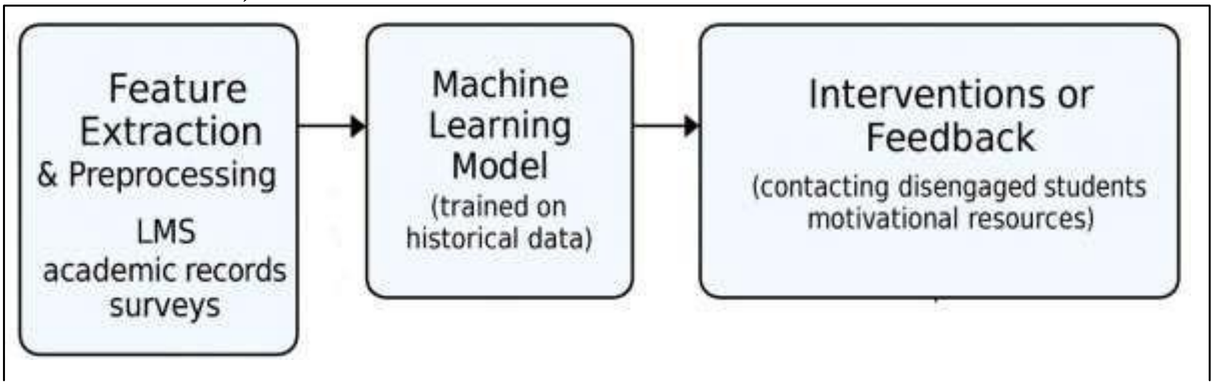

Figure 4: Generic pipeline for predicting student engagement/motivation using machine learning.

In addition to raw activity counts, researchers often engineer more sophisticated features from behavioral logs [79]. Examples include *regularity metrics* (e.g. variance in login intervals, to distinguish steady workers from crammers), *sequence patterns* (the order in which a student accesses materials, which can indicate strategic learning), or *network measures* in forums (like centrality of a student in discussion threads). These derived features can provide deeper insight into engagement quality, not just quantity. For instance, a student who always accesses the lecture notes *before* attempting quizzes might be more cognitively engaged in effective study strategies than one who does so in reverse. Some studies have also incorporated *text analysis* of discussion posts or messages to gauge engagement [80]. For example, analyzing the sentiment or emotion in forum posts can reflect emotional engagement or frustration. Benabbes *et al.* [4] used a BiLSTM (bidirectional long short-term memory) neural network with FastText embeddings to detect emotions in students' forum posts, incorporating those as part of an engagement prediction model. This kind of NLP feature adds a qualitative aspect to the engagement profile (e.g. a student expressing confusion or enthusiasm in posts) [81][82][83].
Table 1 summarizes the major feature categories used and their prevalence in recent predictive modeling studies. Behavioral LMS log features dominate, followed by academic performance metrics; demographic and especially psychological features are comparatively rare in current literature.

Table 1: Major Feature Categories for Predicting Student Engagement/Motivation

Feature Category	**Description and Examples**	**Usage in Studies**
Behavioral (LMS Logs)	Click-stream and activity data from online platforms. Examples: number of logins, pages viewed, time on task, forum posts made, videos watched, assessments attempted. Indicates participation level and study habits.	Very high (≈92% of studies use LMS log data).
Academic Performance	Course grades and scores on assessments. Examples: quiz/exam scores, assignment grades, overall course grade, GPA. Sometimes prior academic history. Provides context on achievement and can serve as a target or feature.	High (≈41.8% of studies include performance metrics).
Demographic	Background information about students. Examples: age, gender, prior education, socioeconomic status. Can influence engagement patterns (though often indirectly).	Moderate (≈36.7% of studies include some demographic attributes).
Academic Background	Prior academic records and related info. Examples: previous semester GPA, entrance exam scores, academic major, etc. Used to gauge preparedness or baseline ability.	Limited (≈11.4% of studies).
Psychological	Psychometric and affective measures. Examples: personality traits (Big Five scores), motivation/self-efficacy survey responses, learning style inventories, emotional states. Provide insight into internal drivers of engagement.	Rare (≈1.3% of studies) – underutilized due to data collection challenges.

In higher education contexts, especially with large classes, *demographic data* are sometimes available and can be considered. Demographics alone should not be used to draw causal conclusions, but they can help identify patterns or disparities in engagement. For example, some studies have noted differences in online engagement behaviors across age groups or between traditional and non-traditional students, or investigated how first-generation college students engage relative to others. In predictive models, demographic features (like age or gender) have shown only modest incremental benefit, and their inclusion raises considerations of fairness and bias. If used, it is often in aggregate analyses or to ensure that interventions are equitable across groups [84][85].

Academic background features (such as prior GPA, prerequisite course grades, etc.) can improve model accuracy by accounting for student preparedness or ability. A student's past academic performance may correlate with both motivation and engagement in a new course [86]. For instance, a high-performing student entering a course might have strong study skills (leading to high engagement) or conversely might become complacent (leading to lower engagement if the course is too easy) [87][88]. Including such features can help models adjust predictions – some researchers found that using prior academic data helped identify at-risk students more accurately. However, not all studies have access to this data, and some focus on behaviors within a course as the primary indicators [89].

3.2 Personal, Psychological and Other Data

In contrast to the abundant clickstream and grade data, *psychological and personal data* are much less commonly used in ML models for engagement/motivation – but they represent a promising frontier [90]. As shown in Table 1, only about 1% of studies incorporated psychological attributes like personality or motivation questionnaires. One reason is that such data often require administering surveys or tests, which is not always feasible at scale or in real time. Nonetheless, a few notable works have demonstrated the value of these features. The study by Apampa *et al.* [3] is a prime example: it collected students' Big Five personality trait scores and used them to predict their intrinsic and extrinsic motivation levels. The ML models in that work effectively mapped *personality profiles to motivation outcomes*, achieving high accuracy in identifying students' motivational orientations. This suggests that with the right data, we can directly predict motivation, not just infer it from behavior. Similarly, researchers have looked at survey-based engagement scales (where students self-report their engagement or disengagement) and tried to predict those from LMS data, essentially training models to approximate survey results without continuously surveying students. This approach can help validate whether the behavioral metrics truly align with the internal state of engagement.

Other personal data that have been explored include *student attitudes and dispositions* (e.g. self-regulated learning skills, interest in subject, or satisfaction ratings). For instance, one study might use an entrance survey measuring a student's initial interest in the course topic as a feature to predict how their engagement will trend. In general, *open-response or Likert-scale survey data* can be quantified and included in models, though few post-2023 studies have published results on doing so at scale. An exception is when using public large-scale datasets like PISA or national studies: for example, one research group used data from a global student survey to predict self-efficacy (a motivational construct) using ML, finding moderate success with algorithms like XGBoost. However, such analyses are more correlational and not yet common in course-specific early-warning systems [92][93].

One underutilized but potentially rich source of data is *textual and linguistic data from students* (outside of forum emotions already mentioned). For example, analyzing reflective essays or feedback that students write could yield features about their mindset or motivation. Topic modeling or sentiment analysis on course feedback might indicate motivation levels (e.g. a student writing about how they value the course versus expressing apathy). As natural language processing (NLP) techniques advance, we may see more incorporation of these kinds of qualitative data into engagement/motivation models [94].

It's also worth noting the rise of *multi-modal data* for engagement detection, though most examples to date are in controlled research settings. These include using video of students (face and gaze tracking to detect attention), audio (voice tone in class discussions), or even physiological sensors (heart rate, EEG) to measure engagement or affective states. For instance, computer vision techniques have been used to analyze facial expressions and infer when students are bored or disengaged. While such approaches are at the frontier and raise privacy concerns, they illustrate the breadth of data that could inform engagement predictions. A 2023 engagement detection tutorial noted that combining facial emotion recognition with deep learning models allowed real-time prediction of learner engagement with reasonable accuracy. In the coming years, we might see research that fuses these sensor-derived features with traditional LMS data to improve prediction robustness, especially in hybrid learning scenarios [95][96].

4. Machine Learning Models and Techniques for Prediction

Researchers have experimented with a variety of machine learning algorithms to predict student engagement levels and motivation, ranging from interpretable classical models to more complex ensemble and deep learning methods. This section reviews the landscape of ML techniques applied, discusses model performance reported in recent studies, and addresses how models are evaluated. We organize the discussion into supervised learning approaches (classification and regression), deep learning and hybrid methods, and note common evaluation metrics. **Figure 4** later in this section provides a comparative illustration of prediction accuracy achieved by different model types in an example scenario [97][98].

4.1 Supervised Learning Approaches

Supervised classification has been the predominant approach in engagement prediction research. In supervised learning, models are trained on historical student data with known labels (e.g. engagement level, often categorized as "low/medium/high" or "engaged vs not engaged") or target values (e.g. a motivation score). Classification models aim to predict discrete classes such as *"student is disengaged"* or *"student is highly motivated"* based on input features, whereas regression models predict a continuous value (e.g. a motivation scale rating or percentage of activities completed) [99].

According to a recent systematic review [100][101], **88.6% of relevant papers employed classification methods** to predict student engagement or performance. This high prevalence is due to many formulations of the problem being naturally classification: for example, identifying which students are "at-risk" (disengaged) vs "on-track" (engaged), or classifying motivation level (perhaps using a threshold on a motivation scale). Only about 12.7% of studies used pure regression approaches, and these were typically cases predicting a numeric outcome like final exam score (which is more a performance prediction than engagement) or a continuous engagement index. In some cases, researchers converted what could be a regression problem into classification by binning the outcome (e.g. defining engagement categories). Clustering (unsupervised learning) has also been explored to detect patterns of engagement, but usually as a supplement to classification; for instance, clustering students by behavior to define engagement categories, then using classification to predict those categories.

Common classification algorithms used include *Decision Trees (DT), Random Forests (RF) and other ensemble trees, Support Vector Machines (SVM), Naïve Bayes (NB), k-Nearest Neighbors (KNN), and Logistic Regression (LR)*. These algorithms have been popular due to their relative interpretability and effectiveness on tabular educational data. A meta-analysis of recent studies showed that decision trees, random forests, and SVM were among the most frequently employed algorithms (each appearing in roughly 40–45% of studies). For example, a study might train a decision tree to classify students into "low" or "high" engagement based on features like number of clicks, time online, and assignments missed. Decision trees are intuitive for educators to understand – they produce rules like "IF forum posts < 5 and total hours online < 2 THEN disengaged" – which is a desirable property. Random forests (an ensemble of decision trees) often yield higher accuracy by averaging many trees, though at the cost of some interpretability. SVMs have also been applied with success, particularly when the data is high-dimensional or when a clear margin between classes exists in the feature space [101].

In terms of performance, many studies report classification accuracies in the range of ~80–95% for identifying engaged vs disengaged students or for predicting course success using engagement data. For instance, Benabbes *et al.* [4] found that a decision tree model achieved about **98% accuracy (AUC 0.97)** in classifying students' engagement level in an online course. This exceptionally high accuracy was likely in a controlled dataset with clearly separable groups (indeed, they clustered students into distinct engagement profiles before classification). Another study by El-Beshbishi et al. [2] compared nine classifiers on a medical course dataset and reported that *Logistic Regression performed best with 95% accuracy* in predicting student engagement levels. These figures suggest that, at least in some contexts, student engagement (as defined by the study) can be predicted with very high correctness by ML models. It's worth noting that such results can depend on how the engagement "label" was determined – for example, if the label itself is derived from the same behavioral metrics, a model can appear extremely accurate by essentially learning a threshold. In El-Beshbishi et al. [2] case, they defined engagement levels based on participation in activities, and indeed found that the *frequency of logins and content views was strongly related to engagement*, which makes those features highly predictive [102][103].

When multiple classes or continuous values are involved, performance can be more modest. Some studies attempt to predict a numeric engagement score (e.g., a self-reported engagement survey averaged to a 0–100 scale) using regression. The accuracy of such regression models might be reported in terms of RMSE or correlation; for example, a model might achieve an \$R^2\$ of 0.5 in predicting a survey engagement score – indicating moderate success. However, given engagement's complexity, many opt to simplify it into categories for prediction [104].

Multi-class classification is used when engagement is categorized into more than two levels (e.g. low/medium/high engagement). An example is the UCI "Student Performance" dataset (from Kalboard 360 LMS) that some researchers used, which labels student performance/engagement as *Low (L), Medium (M), High (H)*. In one investigation, logistic regression and other classifiers were trained on such a dataset; they needed to handle a three-class classification. Techniques like one-vs-rest or softmax logistic regression can do this directly. Kurniadi *et al.* [11] specifically looked at a regularized logistic regression to predict multi-class student performance categories and found it effective. They emphasize addressing class imbalance in such multi-class contexts (since often the "High" engagement group might be much smaller than the "Low" or "Medium"). In general, multi-class engagement classification can be more challenging, and researchers sometimes report precision/recall for each class to show, for example, that *High-engagement students are predicted with 90% precision but Low-engagement with only 75%*, etc [105].

Figure 5 provides a hypothetical comparison of several popular ML algorithms' accuracy in predicting student engagement on an example dataset. (These values are illustrative; actual performance varies by context.) As shown, decision tree and random forest models often perform strongly, with ensemble methods typically a few points more accurate than single models. Simpler models like Naïve Bayes may lag slightly in accuracy but can still be in a useful range. What specific model works best has differed across studies – there is no single winner for all contexts. For instance, while El-Beshbishi et al. [2] found logistic regression to be top in their case, other studies have found decision trees or boosting models to outperform. A benchmark from one review indicated that *ensemble methods generally outperform individual classifiers in educational predictions*, echoing a common theme in ML [106].

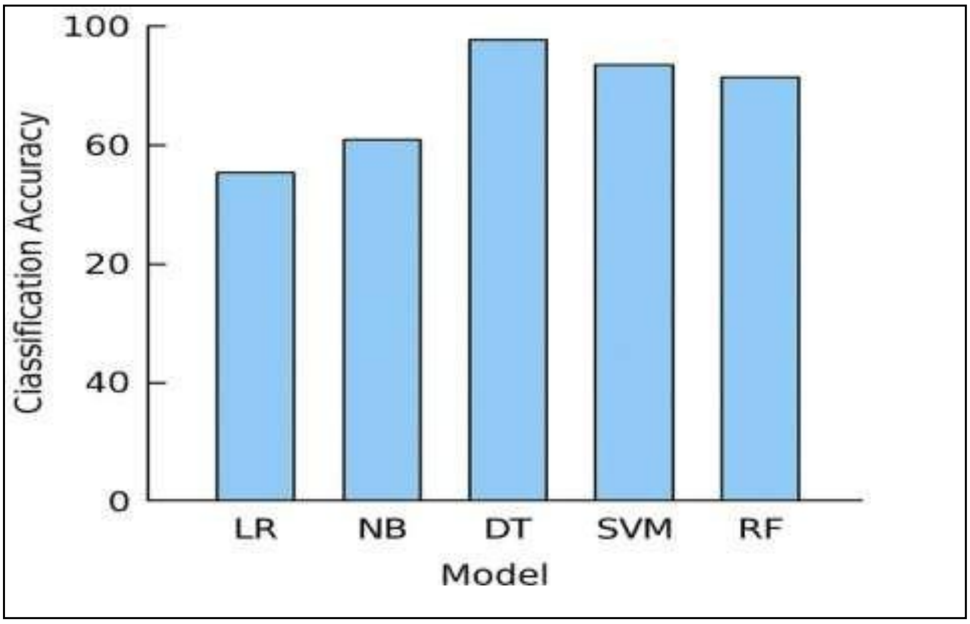

Figure 5: Comparison of classification accuracy for different ML models predicting student engagement

Beyond accuracy, other evaluation metrics are crucial in educational contexts. Models are often evaluated on *precision, recall, F1-score, and AUC (Area under ROC Curve)*, especially when dealing with imbalanced classes (e.g. far fewer disengaged students than engaged). Commonly reported metrics in recent studies include precision and recall in the 0.8–0.95 range for the majority class and somewhat lower for the minority class. For example, the medical course study reported precision = 100% and recall = 88.4% for the positive class (engaged) when using the best model, indicating it was very precise in identifying engaged students but missed some (recall ~88%). Such detailed metrics are important if an intervention is to be based on the predictions – one might prefer a model with slightly lower accuracy overall if it ensures higher recall of at-risk (disengaged) students, to not miss those who need help [107].

It's also worth noting that *class imbalance* is a common issue; often only a small fraction of students are labeled as "disengaged" or "at-risk" in a given dataset. Researchers have used techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance training data. Rozi *et al.* [7] specifically explored resampling methods for imbalanced educational data and found that applying SMOTE significantly improved model accuracy for minority classes. This suggests that careful handling of class imbalance is essential to avoid models that simply predict the majority class (e.g. labeling everyone as engaged and achieving high accuracy because most were engaged, but failing to identify the truly disengaged ones). Many studies thus report metrics like F1 or AUC which are more informative under imbalance than raw accuracy. According to one review, *accuracy and F1-score* are the most common metrics, used in 75% and 57% of studies respectively, followed by precision and recall [108].

4.2 Deep Learning and Advanced Models

While classic ML algorithms have dominated, there is a growing trend of applying *deep learning* techniques and advanced models in this domain, particularly as datasets become larger and more complex (e.g., MOOCs with tens of thousands of students, or multimodal data). Deep learning can capture non-linear relationships and temporal patterns that might be present in engagement data (for instance, sequences of actions over time) [109]..

One area where deep models excel is in analyzing sequential or time-series data of student interactions. For example, *recurrent neural networks (RNNs)* and their variants (like LSTM and GRU) have been used to model the sequence of student activities and predict future engagement states or even grades. Another application is using *Convolutional Neural Networks (CNNs))* or other deep architectures for specialized data types. For instance, if we have clickstream data represented as an image or matrix (students × activities), a CNN might detect patterns of engagement. More concretely, CNNs have been used for *visual data* in engagement detection: some works feed video frames of students' faces into CNNs to classify engaged vs not engaged. While that is more an *affective computing* approach, it intersects with our topic when combined with other data [110].

Deep reinforcement learning (DRL) has also made an entry in student performance/engagement prediction. Bagunaid *et al.* [8] proposed a DRL-based early warning system for student performance. In their approach, a deep RL model learned to trigger alerts for at-risk students in a smart education setting. Although their focus was on performance, engagement data was part of the input, and the system essentially "learned" optimal policies for when to warn about disengagement/performance issues. This is an advanced use-case, but it demonstrates the expanding toolkit beyond standard supervised learning [111]. DRL could be particularly useful for *prescriptive analytics* – not just predicting engagement, but also learning what interventions to apply to improve engagement (treating it as a sequential decision-making problem).

One cannot overlook *ensemble and hybrid methods* under advanced models. Ensemble methods like *Gradient Boosted Trees* (e.g. XGBoost, LightGBM) have gained popularity for their strong performance on structured data. In educational data mining competitions, boosted tree models often rank near the top. These models can handle nonlinear interactions and typically yield higher accuracy than single models. For example, in El-Beshbishi et al. [2], in addition to Logistic Regression being best, they also tested a Gradient Boosted Tree which was among the top performers (though slightly below LR in that case). Another advanced technique is **stacking** (ensemble of ensembles), which was used by some researchers to combine predictions from multiple base learners. Manzali *et al.* [9] explored a hybrid model combining Random Forest and Naïve Bayes for student performance prediction, noting that this ensemble improved predictive accuracy over either model alone. The rationale is to capture complementary strengths: for instance, a random forest might capture complex interactions, while a Naïve Bayes brings probabilistic simplicity that could generalize better in some cases. They found the RF+NB hybrid achieved better performance than either individually. This exemplifies the general trend that *ensembles generally outperform single models in educational data prediction [112]*.

With deep learning, a challenge is interpretability. Educators and stakeholders often prefer simpler models that provide understandable rules or feature importances. There is thus interest in **Explainable AI (XAI)** techniques applied to educational ML. For example, researchers have begun using *SHAP (SHapley Additive exPlanations)* values or rule extraction from tree ensembles to explain why a model predicted a student as disengaged. Chong et al. [1] noted that the lack of consensus on engagement levels and definitions hampers the use of explainable AI – i.e., it's hard to build interpretable models when even the construct is not uniformly defined. Despite that, having interpretable models is crucial for trust in academic settings. For deep models, one might use techniques like attention mechanisms to highlight which time steps or features contributed most to an engagement prediction [113].

In terms of *performance*, deep and advanced models have had mixed results depending on context. In some studies with enough data, deep learning outperforms classical methods. For instance, a *neural network model* might slightly outperform logistic regression in predicting course completion based on clickstream (perhaps capturing nonlinear effects of feature combinations). However, many educational datasets are moderate in size (hundreds or a few thousand students), where deep learning does not always significantly outperform well-tuned classical models, and sometimes performs worse if data is limited. Chen *et al.* [5] observed that *ensemble methods generally outperform single models* in terms of accuracy, but they did not note a clear dominance of deep learning over ensembles of trees in current literature. This suggests that for structured tabular data (typical in LMS logs), tree ensembles remain extremely competitive. Deep learning shines more when handling unstructured data (text, images) or sequential patterns [114].

As an example, one 2024 study applied an LSTM to predict student engagement weekly in a MOOC and achieved an F1-score slightly higher than a baseline random forest, but the improvement was modest and came at the cost of complexity. On the other hand, for analyzing discussion forum text to infer engagement, a deep learning NLP model (e.g. Transformers) could uncover nuanced indicators (like expressing boredom or excitement) that simple keyword approaches might miss.

To evaluate advanced models, researchers use the same metrics as before (accuracy, F1, AUC, etc.). It is common to see cross-validation used for model training given the often limited data, and hyperparameter tuning via grid search or Bayesian optimization to get the best out of each model. Reporting of results usually includes a comparison of multiple models (as in Figure 4, albeit hypothetical, such comparisons are the norm in papers to demonstrate improvement) [115].

4.3 Model Evaluation and Performance Metrics

Evaluating the performance of ML models in predicting student engagement and motivation involves several standard metrics and considerations unique to educational settings. As noted, *accuracy, precision, recall, F1-score, and AUC* are commonly reported. However, it is crucial to interpret these metrics in the educational context. A model with slightly lower overall accuracy but higher recall of disengaged students might be preferable if the goal is to catch all students who need help (even at the cost of some false alarms). On the other hand, too many false positives (low precision) could burden instructors with unnecessary interventions. Therefore, researchers often seek a balance (F1-score) or consider domain needs (e.g., maximizing recall for at-risk identification, while maintaining acceptable precision) [116].

It is also common to use *cross-validation* or separate training/validation/test splits to ensure models generalize beyond the specific cohort. Some studies explicitly test models across different courses or semesters (to check generalizability). For instance, a model trained on last year's class is tested on this year's class data to see if it still accurately predicts engagement – an important step if the model is to be deployed in practice. Issues like *concept drift* (where the meaning of engagement indicators might change over time or different instructional contexts) are a challenge. Recent work reviews approaches to handle non-stationary data streams in educational settings. While not the focus of this paper, it's worth noting that maintaining model performance as courses evolve or as teaching methods change is an active area of research.

In the studies reviewed, many models achieved strong metrics on retrospective data. For example, classification AUCs above 0.90 are commonly reported, indicating the model can discriminate engaged vs disengaged students very well. The true test, however, is deploying these models live and seeing if the predictions hold and can usefully guide interventions. Some institutions have begun pilot programs integrating predictive models into dashboards for instructors, often focusing on predicting course *dropout or failure* (which correlates with disengagement). These early warning systems, if well-calibrated, have shown potential to improve student outcomes by enabling proactive support [117].

From an academic standpoint, Table 2 in the next section will enumerate a few representative research works, including their algorithms and results, to concretize the discussion. Before that, we conclude Section 4 by reinforcing that numerous ML techniques – from decision trees to deep neural networks – have proven effective in modeling student engagement and motivation. The specific choice depends on data characteristics and the needs for interpretability. As the field moves forward, we anticipate more hybrid models (combining, say, deep learning for feature extraction from unstructured data with interpretable models for the final prediction) and a continued emphasis on transparent algorithms that educators can trust.

5. Practical Applications and Discussion

Predictive models of student motivation and engagement are most valuable when their insights are translated into actions that improve student learning. In this section, we discuss how the outputs of the machine learning approaches described above can be applied in educational practice. We focus on three main areas: early warning and intervention systems, personalized and adaptive learning, and a discussion of challenges (such as ethical considerations and the need for alignment with pedagogy) along with future research directions. Throughout, we emphasize that the goal of these models is not merely prediction for its own sake, but to enable more responsive, supportive, and effective teaching and learning strategies [118].

5.1 Early Warning Systems and Targeted Interventions

One of the clearest applications of engagement/motivation prediction is in *Early Warning Systems (EWS)* for at-risk students. These are systems that alert instructors, advisors, or students themselves when a learner is predicted to be disengaged or poorly motivated, so that timely support can be provided. Many institutions are implementing learning analytics dashboards that incorporate predictive models to flag students who may need help. The research presented in earlier sections provides the backbone for such systems: by monitoring LMS logs and other indicators in real time, a trained model can classify whether a student's engagement level is low (relative to successful patterns) even after a few weeks of classes. If the model's prediction crosses a risk threshold, the system can trigger an alert or recommendation [119].

Studies suggest that early identification of disengagement can significantly improve student outcomes. For instance, if a model predicts by week 3 that a student is likely to disengage (based on low login frequency, few interactions, or other features), an instructor can reach out to that student personally, inquire about challenges, and encourage or guide them before it is too late in the semester. Chong et al. [1] noted that through prediction models, instructors are *"enabled to recognize disengaged students early and foster their needs towards learning"*. This might involve offering additional tutoring, clarifying misconceptions, or simply motivating the student with encouragement and emphasizing the relevance of the material. In practice, some universities have adopted systems where instructors receive a list of students "at risk of failing or dropping" each week, computed via predictive analytics; these lists often align closely with those students showing signs of disengagement (missing activities, etc.) [120].

There is evidence that such interventions can make a difference. A review of 38 learning analytics dashboard studies found medium-to-large effects on student *participation* after dashboards were introduced – implying that when students and instructors are given feedback on engagement, it can prompt increased participation. For example, Kaliisa *et al.* [10] reported that certain dashboard interventions led to improved student engagement in some studies, though they also cautioned about methodological issues in others. The key is that simply predicting is not enough; *closing the loop* with action is essential. If an algorithm predicts a student is disengaging but no one responds to that information, it does not benefit the student. Therefore, early warning systems must be integrated with workflow: advisors might schedule a meeting with the student, or the system might send the student a gentle nudge email like *"We noticed you haven't logged in much this week; remember that consistent practice is important. Can we help you get back on track?"*.

Another aspect is prioritization. In large classes, instructors can't always closely monitor everyone. A good predictive system can focus the instructor's attention on a manageable subset of students who are most likely in need of help (the *precision* aspect). For instance, rather than manually scanning hundreds of students' activity logs, an instructor might check the top 5–10 students flagged by the model as having low engagement and reach out to them. Even if the model isn't perfect, this directed approach is far more efficient than unguided attempts. In El-Beshbishi et al. [2] deployment, they found that using RapidMiner to classify students as engaged or not allowed accurate identification of non-engaged students, which could then be targeted [119][120].

5.2 Personalized and Adaptive Learning

Beyond reactive interventions, engagement and motivation predictions can feed into *personalized and adaptive learning systems* that proactively adjust the learning experience to each student's needs. The idea is to use the model's ongoing assessment of a student's engagement/motivation to tailor content, pace, or support, thereby keeping the student more engaged and motivated.

For instance, an intelligent tutoring system (ITS) or adaptive e-learning platform might monitor a student's interaction. If the model predicts the student's engagement is dropping (perhaps they started skipping optional exercises, or their quiz performance is deteriorating alongside reduced activity), the system could respond by altering the learning path. It might present a motivational message, introduce a more interactive element (like a short educational game or simulation) to rekindle interest, or adjust difficulty if the student appears frustrated. This aligns with the concept of *adaptive engagement strategies*. Research in this area often leverages reinforcement learning: the system "learns" which actions (e.g., showing a hint, giving encouragement, presenting a challenge problem) best increase a given student's engagement metrics. For example, a deep reinforcement learning model might decide to show a struggling student a simplified problem to build confidence (thus boosting motivation through a sense of competence) [114][115].

Personalization can also mean recommending different content based on motivation profiles. A student predicted to be highly intrinsically motivated might be given enrichment activities to further feed their curiosity (since they'll likely engage deeply with them), whereas a student with low motivation might be given more scaffolded, gamified tasks to provide immediate extrinsic incentives and gradually cultivate interest. Another application is forming adaptive groups or peer mentoring. If some students are predicted to be disengaged, the system might pair them with highly engaged peers for group work, under the hypothesis that peer influence could increase their engagement. There are studies on *adaptive collaborative learning support* where group composition or prompts are adjusted based on engagement levels to ensure balanced participation.

Recommender systems for learning resources can use engagement as part of the utility function. An AI tutor might say, "students with similar profiles to you found this supplemental video engaging." This merges collaborative filtering with engagement prediction to ensure recommendations are not only relevant to the learning objective but also likely to spark the student's interest. Recent advances in explainable recommendations (e.g., "because you spent a lot of time on topic X, you might enjoy this advanced reading") tie into keeping the student motivated by autonomy and relevance [117].

Adaptive systems need continuous input from the predictive models – essentially closing a feedback loop: the model predicts low engagement, the system adapts content, which hopefully improves engagement, which then is observed by the model, and so on. There is a strong parallel here with *learning companion* or *affective computing* systems that attempt to detect a student's affective state (boredom, confusion, flow) and respond appropriately. Engagement prediction is a form of that (engagement often correlates with affective states like interest or confusion). In terms of results, some adaptive platforms have reported improved learning gains when incorporating engagement-aware adjustments. For instance, an adaptive reading system that monitored student engagement (via eye-tracking and comprehension quiz results) and adjusted reading difficulty accordingly led to higher overall comprehension scores than a non-adaptive version. Though that example goes beyond just ML prediction (it includes hardware sensors), it underscores the potential: by keeping students in an optimal zone of engagement (not too bored, not too frustrated), adaptive systems can improve learning.

5.3 Challenges and Future Directions

While the use of ML models to predict and enhance student motivation and engagement is promising, several challenges must be addressed to fully realize their benefits. We outline some key issues and future research directions:

Data Privacy and Ethics: Educational data, especially when it includes sensitive information like psychological traits or demographics, must be handled with strict privacy safeguards. There is a fine line between helpful monitoring and a "big brother" effect. Students (and faculty) may justifiably worry about how their data is used, who can see the predictions, and whether mistakes could unfairly label them. Ensuring transparency and obtaining informed consent are crucial when deploying these models institution-wide. Moreover, any automated intervention should ideally involve a human in the loop for high-stakes decisions. Future research may explore privacy-preserving modeling techniques (like federated learning, where models train across institutions without sharing raw data) to alleviate privacy concerns while still leveraging broad data.

Bias and Fairness: ML models can inadvertently perpetuate or even amplify biases present in training data. If historically certain groups of students had lower engagement (perhaps due to extrinsic factors like work commitments or a non-inclusive curriculum), a naive model might simply learn to predict disengagement for those groups, leading to a self-fulfilling prophecy (they receive more alerts, possibly feel stigmatized, and remain disengaged). Ensuring fairness means the models should be tested for bias across groups (gender, ethnicity, etc.) and perhaps incorporate bias mitigation strategies. For example, one could use balanced training sets or add fairness constraints so that the false positive/negative rates are similar across groups. Additionally, engaging with the root causes of disengagement in different groups – something an algorithm alone can't do – is important. As a trivial example, if commuter students appear less engaged because of schedule constraints, the solution might be structural (flexible deadlines or online resources), not just flagging them as at-risk [108].

Model Interpretability: As mentioned earlier, a significant challenge is that many powerful models (neural networks, ensembles) are black boxes. Yet, educators often want to know *why* the model predicts a student is disengaged, to take appropriate action. Efforts in explainable AI need to be applied here, providing *human-readable rules or feature importance*. Chong et al. [1] highlighted that the lack of consensus on how to define or quantify engagement makes it harder to have clear explanations. Future work could involve developing standard engagement indices or levels (perhaps akin to standardized tests for engagement) that models can align with, making outputs more interpretable [121].

Cold Start and Generalizability: A practical issue is that predictions are difficult for *new students or new courses* where no historical data exists. A model trained on past offerings of a course might not directly apply to a brand new course (different content, structure) or a brand new student population (e.g., if a university admits a significantly different cohort one year). Future research may focus on *transfer learning* – adapting models to new

courses by transferring knowledge from similar courses. Also, incorporating domain knowledge (e.g., known pedagogical factors that affect engagement) could help models generalize better beyond their training data [102].
Multi-modal and Multi-dimensional Engagement: So far, most predictive models focus on quantitative log data and perhaps some survey results. But engagement is multi-faceted and complex. Integrating *multi-modal data* (text from discussion forums, sentiment from student feedback, video-based attention tracking in live classes, etc.) could provide a more holistic view of engagement. For example, analyzing *qualitative feedback or reflection essays* with NLP might reveal motivational shifts that raw click data cannot. A future direction is to combine such data in a coherent model – perhaps using deep learning to fuse different feature types (vision, text, numerical) – to improve predictive accuracy and depth of understanding. This is technically feasible but again raises privacy/acceptance issues that must be carefully navigated [103].
Integration with Theory: Another challenge, as noted by Gašević *et al.* [12], is that *learning analytics must become more rigorous in adopting educational theory*. Predictive models should ideally be informed by theories of motivation (like SDT) and engagement, not just purely data-driven correlations. This can guide feature selection (e.g., include features that correspond to autonomy, competence, relatedness needs) and interpretation of results. Future research might blend ML with *educational modeling* – for instance, using cognitive or motivational models (perhaps Bayesian Knowledge Tracing or similar) in conjunction with ML to better predict and support student engagement. By incorporating theory, models can also suggest *why* a student is disengaged: is it a motivation issue (they don't see value), a self-regulation issue (poor time management), or a social integration issue (feeling isolated)? Addressing those root causes requires more than numbers; it needs qualitative insight and theoretical frameworks [104].
Continuous Improvement and Feedback Effects: When predictive systems are deployed, they can change the very behavior they measure (students might engage more once they know they are being monitored or after receiving an intervention). This feedback loop means models may need continuous recalibration. Also, measuring the *impact* of these systems requires careful experimental or quasi-experimental studies. Some early studies reported improvements in course grades and retention when using predictive alerts, but others found no effect or even negative effects if not implemented well. It's an ongoing research direction to determine the best practices for using predictions to actually drive positive behavior change. For instance, how to word alert messages to be motivating rather than discouraging? What is the optimal timing for interventions (immediately after a dip in engagement vs periodic summaries) [105]?
The *future directions* point toward more human-centric and theory-driven approaches: explainable and fair models, integrated with pedagogical interventions, continually refined through feedback, and evaluated for actual impact on learning and retention. If these challenges are met, predicting and improving student motivation and engagement through machine learning could become a standard, valuable component of higher education, especially in large or online classes where traditional personal monitoring by instructors is difficult. As Pooja et. al [6] notes in an analysis of AI in education, we are at the cusp of an era where intelligent systems can transform learning by making it more personalized and responsive. The research work surveyed here provides a solid foundation, and the coming years will likely see these methods mature and integrate seamlessly into educational practice. Table 2 highlights a few representative studies, their context, methods, and key findings.

Table 2: Selected Recent Research Works on Predicting Student Engagement and Motivation

Study (Year)	**Focus & Context**	**Data & Features**	**ML Methods**	**Key Results**
Apampa *et al.* [3]	Predicted academic motivation (intrinsic, extrinsic, amotivation) among university students (UK/Nigeria). Focus on higher education computer science/business students.	Personality traits (Big Five survey), demographic info; Motivation questionnaire as labels (AMS).	Compared regression models, decision trees, and neural networks to map personality → motivation.	Models accurately predicted motivation levels (high R^2). Found Conscientiousness & Openness positively predicted intrinsic/extrinsic motivation, while Neuroticism correlated with amotivation. Demonstrated ML can identify students who may need support to improve motivation.
Benabbes *et al.* [4]	Predicted engagement level of e-learning students in online courses (Morocco). Aimed to detect and track disengaged learners in real time.	LMS interaction data (e.g. number of forum posts, time spent online). Extracted text sentiment from forum posts (emotion via BiLSTM). Clustered students into	Multi-step: unsupervised clustering to define engagement levels; then supervised classification. Tested several classifiers (DT, SVM, etc.).	Achieved ~98% accuracy with a Decision Tree in classifying students' engagement level. Noted most learners were "observers" and revealed a nonlinear correlation between engagement and success (moderate engagement linked to performance up to a point). Demonstrated importance of

Study (Year)	Focus & Context	Data & Features	ML Methods	Key Results
		engagement groups for labels.		combining behavioral and emotional features.
El-Beshbishi et al. [2]	Assessed medical student engagement in a first-year course and predicted its impact on performance (Egypt). Implemented an early warning setup in a basic science course.	LMS activity data (frequency of content views, activity completion) and assessment scores. Labeled students by measured engagement level in course activities.	Trained and evaluated 9 classifiers (Naïve Bayes, Logistic Regression, Decision Tree, Random Forest, SVM, Gradient Boosted Tree, etc.) using RapidMiner.	Logistic Regression performed best – 95% accuracy, precision ~100%, recall ~88% for engaged class. Highly engaged students scored significantly better on exams than low-engagement peers. Validated that login frequency ("number of logins") strongly correlates with engagement. The system accurately classified students as engaged vs. non-engaged, enabling timely instructor interventions.

6. CONCLUSION

Our comprehensive analysis shows that these models are not ends in themselves, but catalysts for action. Early warning systems can alert instructors to students who might otherwise "fall through the cracks," enabling proactive mentoring and support. The convergence of machine learning and learning analytics heralds a new era of data-informed teaching and learning. By objectively and continually assessing how students engage and what drives them, we can move toward more responsive education systems that cater to individual needs without sacrificing scalability. Machine learning models, when used as supportive tools, have the potential to amplify educators' ability to foster these qualities in students. The research synthesized in this paper demonstrates substantial progress post-2023 in model accuracy and application breadth. With continued refinement and ethical vigilance, predicting and enhancing student motivation and engagement through machine learning will become an integral component of effective higher education practice, leading to more students not only succeeding in their studies but finding genuine fulfillment in the learning process.

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