# An AI-Inspired Approach to Student Performance Assessment

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## Abstract

This study leverages Artificial Intelligence (AI) methodologies to enhance Human Learning (HL) outcomes. Such AI concepts as weak and strong learners, learnability, and boosting are examined. Weak learners are rudimentary Machine Learning (ML) models that predict only slightly better than random chance, whereas strong learners achieve high performance after undergoing iterative training. Similarly, students with limited prior knowledge (weak learners) can be transformed into strong learners through ongoing structured feedback delivered throughout an educational program. The significance of feedback in both AI and human learning is emphasized. Additionally, motivation is recognized as another crucial factor in achieving learning success. The study advocates AI-inspired performance assessment methods that reward rapid progress, helping initially weaker students catch up with their initially more knowledgeable peers. The findings suggest that AI-inspired strategies can foster more effective, fair, and rewarding learning environments.

*Keywords:* AI-inspired learning, performance assessment, feedback in education, learnability, motivation

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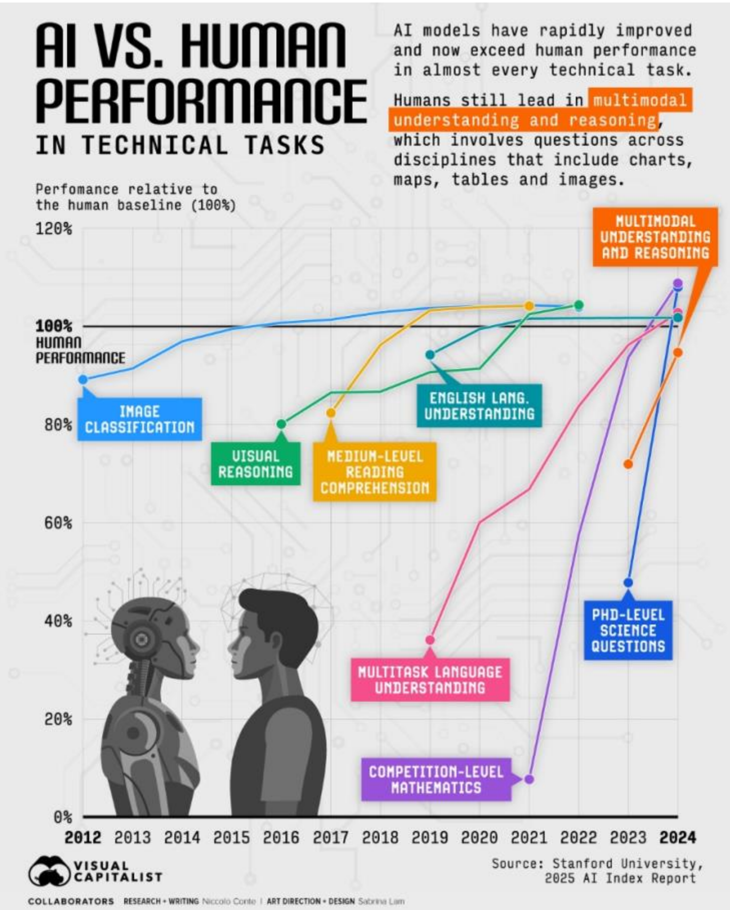
## Introduction

Educational researchers agree that prior knowledge, motivation, cognitive skills, and teaching strategies contribute to learning outcomes. According to Ausubel (1968), the National Research Council (2000), and other sources, prior domain knowledge is considered the most critical determinant of learning success. More recent sources, e.g., Brod (2021), Simonsmeier et al. (2022) admit that prior knowledge may have "positive, negative, or negligible effects on learning." Yet, they came short of ranking the contributing factors by their importance. The motivational factor plays a crucial role, as noted by Pintrich (2003) and Usher and Kober (2012), meaning that prior knowledge alone cannot guarantee success without strong motivation.

Artificial Intelligence/Machine Learning (AI/ML) has grown to rival the human brain in many aspects of intelligence, as seen in **Figure 1**, and has even surpassed human intelligence in many complex tasks. This study explores the potential benefits for human learning derived from advances in AI/ML. If basic computer hardware with clever training algorithms can perform well starting virtually from scratch, the same should be true for humans with motivation and cognitive skills. The goals are to identify conditions for more consistent and positive learning outcomes across learners with different backgrounds and to develop practical strategies for motivation assessment and performance evaluation using targeted feedback.

**Figure 1**
*AI vs. Human Performance in Technical Tasks*




*Note*: AI is surpassing human performance in various technical tasks (clipart is from Zhu, 2025).

## Approach and Methods

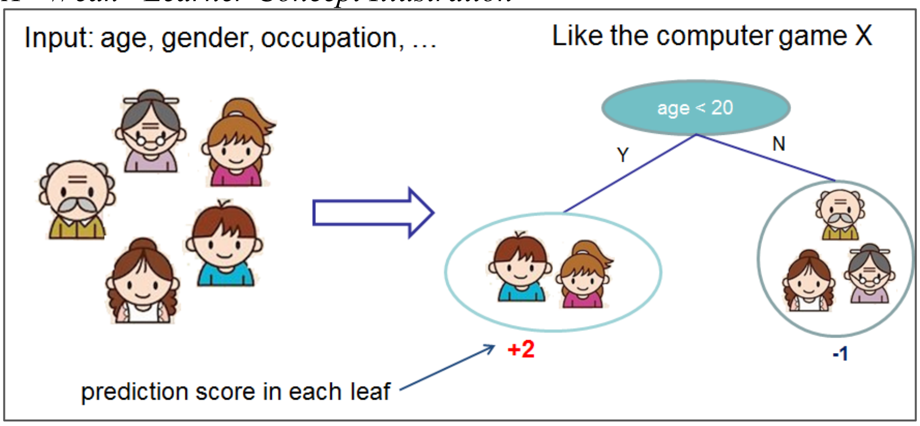
AI/ML learning paradigms have drawn inspiration from human cognitive processes since the early days of AI/ML, when the first artificial neuron circuit was modeled after a simplified biological one (McCulloch & Pitts, 1943). Nikolaidis (2018) outlined similarities between humans and machine learners. Neftci and Averbeck (2019) stated that there is considerable room for the exchange of ideas between biological and artificial learning. Goyal and Bengio (2020) suggested that studying human inductive biases could inspire AI research.

In reversal of the traditional AI/ML learning paradigm, this study draws inspiration from advanced AI/ML to refine the boundaries of what it takes to achieve human learning outcomes.

### "Weak" Versus "Strong" Learners

Schapire (1990) described weak learners as AI/ML models that perform slightly better than random guessing, while strong learners can attain high accuracy. An example of a simple decision tree "stump," representing a weak learner, is shown in **Figure 2**. Boosting techniques convert weak learners into strong ones through iterative training (Freund & Schapire, 1997; Friedman, 2001). Other AI/ML methods, such as Artificial Neural Networks (ANN), e.g., Rumelhart et al. (1986), or Reinforcement Learning, e.g., Neftci and Averbeck (2019), can be applied for the same purposes. This idea is especially relevant to human learners, as structured feedback during training can turn those with weaker prior knowledge into stronger ones.

**Figure 2**
*A "Weak" Learner Concept Illustration*




*Note*: An example of a decision tree that predicts whether a person likes computer games based on a single condition (their age < 20), among many other features. Such a model would likely perform only slightly better than random guessing. However, it would not be accurate for, say, older game fans (clipart is from Mu, 2024).

**Table 1**
*Weak vs. Strong Learner Concepts*

| AI/ML Context | Human Learning (HL) Context |
|---|---|
| A "weak" learner is a simple model that consistently predicts only slightly better than random guessing on a given task. | A "weak" learner is a human with limited prior knowledge about a given subject. |
| A "strong" learner is a model that achieves arbitrarily good performance. | A "strong" learner is a human who attains a robust and comprehensive understanding of a given subject. |
| Boosting, reinforcement learning, and error propagation techniques transform weak learners into strong ones by using gradients as corrections. | An active feedback role will be discussed later. |

**AI/ML: Boosting Methods**

Boosting methods are used to train weak learners until they become strong learners. The Gradient Boosting (GB) method focuses on reducing prediction errors (Friedman, 2001), iteratively improving models to increase accuracy. Another boosting method, AdaBoost, increases the weight of incorrectly classified instances, making them more influential in the subsequent steps of modeling (Freund & Schapire, 1997). These methods can inspire human learning strategies.

Instead of building a single, ultimate, and powerful predictive model all at once, boosting methods iteratively improve models based on errors from earlier iterations. Often, an intermediate model $f_m(x)$ created at $m$-th iteration is considered one of the models contributing to the final model. In our view, the final boosting model can be seen as an ensemble (composite) of all earlier iterations.

$$F_m(x) = F_{m-1}(x) + f_m(x) \tag{1}$$

The boosting approach's premise is that these composite models gradually improve by incorporating one weak model after another, eventually becoming a single strong composite model.

***Gradient Boosting***

GB is a boosting algorithm's flavor focusing on prediction errors (residuals). A current "weak" model $f_m(x)$ is used to tweak the previous model $F_{m-1}(x)$ by $\Delta_m(x)$ to nudge the model predictions towards the actual target, see **Figure 3**. After several iterations, the overall cumulative model becomes an increasingly stronger predictor. In the notation above, the tweak $\Delta_m(x)$ represents a gradient, i.e., a signed rate of change of the loss function $L$. The latter quantifies a discrepancy between the predicted and the true values of $y$. Among loss functions, the most common is the Mean Squared Error (MSE) calculated across all $N$ instances of the feature vector $X$, see (2):

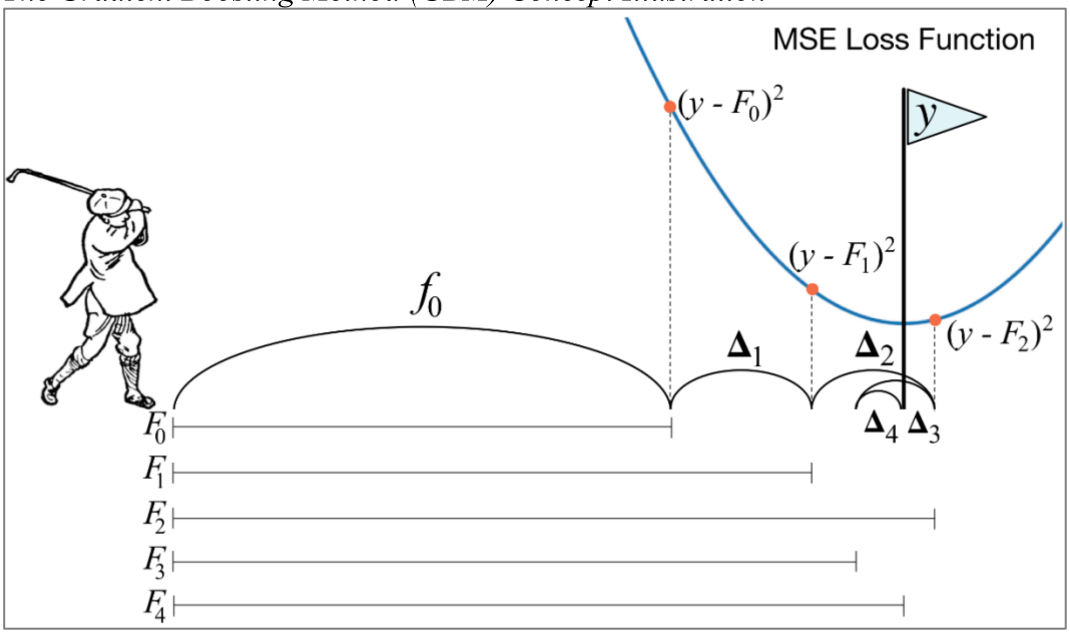
$$L(y, F_M(X)) = \frac{1}{N}\sum_{i=1}^{N}(y_i - F_M(\mathbf{x}_i))^2 \quad (2)$$

To calculate the optimal amount of tweak, a gradient descent optimization method is typically used to minimize the $L$. At each iteration, we update the position by adding a negative gradient scaled by the learning rate, $\eta$ (eta), to better control the process of $L$ minimization. Equation (3) shows the composite gradient boosting model $F_M$ expressed recursively:

$$F_m(x) = F_{m-1}(x) + \eta\Delta_m(x) \quad (3)$$

Every time we add a new weak model to the composite model $F_M$, we hope to nudge our prediction $F_M$, towards the target $y$. Predictions will gradually decrease in step size until they finally converge on $y$, see (Parr & Howard, n.d.). The analogy with the learner is that with each step, the goal gets closer. GB-inspired learning strategies are discussed in Chapter **HL Strategies Inspired by AI/ML**.

**Figure 3**
*The Gradient Boosting Method (GBM) Concept Illustration*

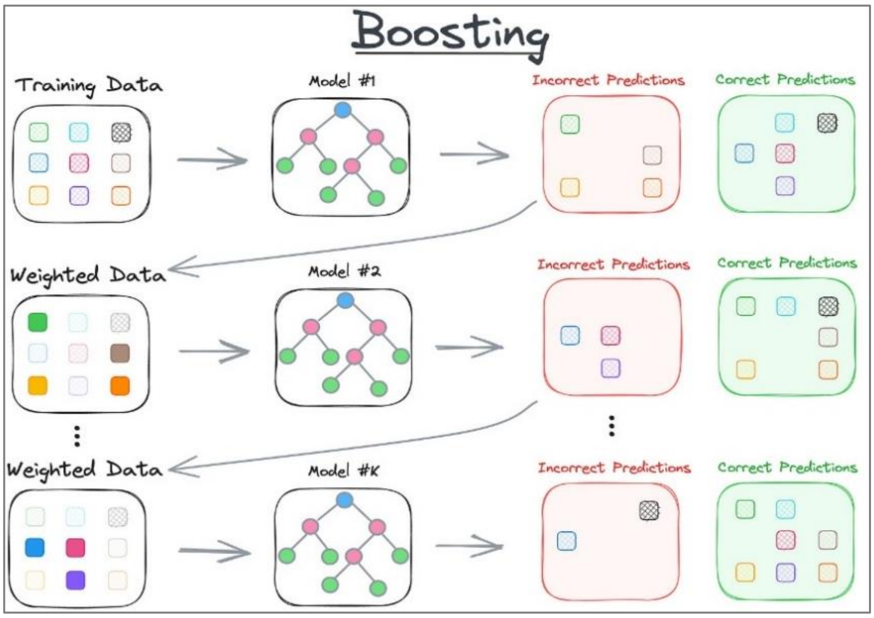



*Note*: The gradient boosting method converges on its goal through a gradient descent process, similar to a golfer aiming for the hole $y$. At each step (golfer's shot), the move is in the opposite (negative) direction of the slope of the MSE (Mean Square Error) loss function's gradient (clipart is from Parr & Howard, n.d.)

***"Adaptive Boosting" – AdaBoost (Freund & Schapire, 1997)***

AdaBoost uses the same idea of combining weak learners to iteratively reduce prediction errors, eventually creating a strong predictor (learner), similar to the Gradient Boosting Method (GBM). However, it employs a slightly different approach to managing prediction errors throughout the iterations. Specifically, it increases the weight of misclassified instances, boosting their importance for the next model in the sequence (the next learning phase), as discussed in Glorot and Bengio (2010). AdaBoost-inspired strategies are covered in Chapter ***AdaBoost-inspired***.

**Figure 4**
*AdaBoost Method*




*Source*: STEM Learning (2023).

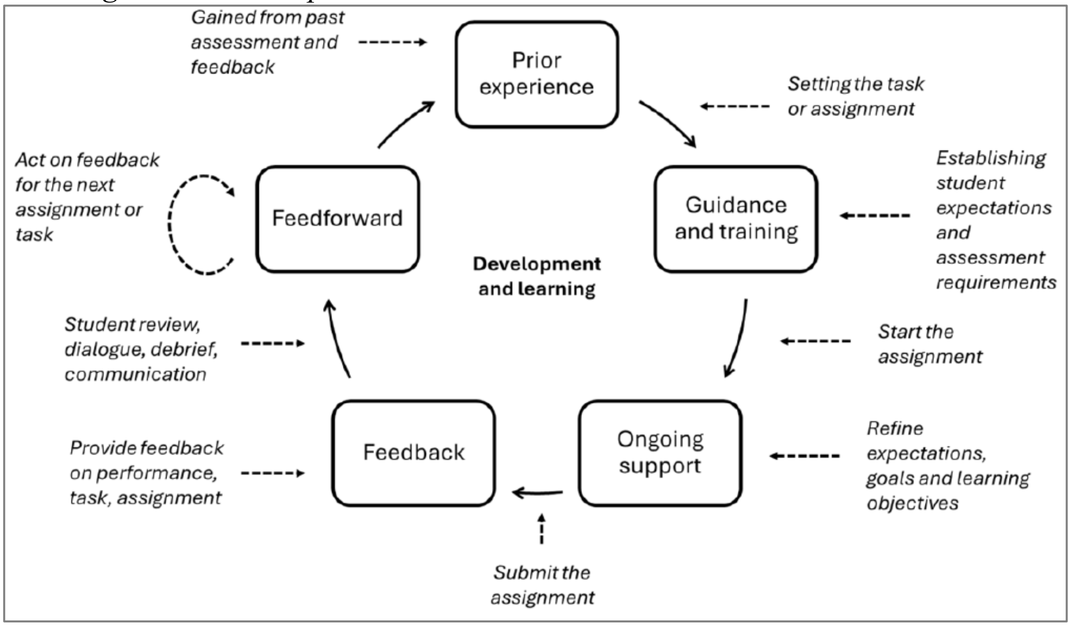
## AI/ML: Artificial Neural Networks (ANN) and the Gradient Flow

Gradient descent optimization is essential for training ANNs with the backpropagation algorithm to minimize the loss function. A smooth flow of gradients (feedback) between layers has been a key requirement for successful ANN training, e.g., (Jha et al., 2021; Rumelhart et al., 1986). However, an ANN's gradient flow can be obstructed due to design or implementation issues, leading to vanishing or exploding gradient problems that cause slow weight updates and poor model performance (Glorot & Bengio, 2010).

## The Feedback Role in AI/ML and HL

Feedback is central to both AI/ML and HL (Human Learning), e.g., Kearns and Vazirani (1994), Hattie and Timperley (2007), Lipnevich and Panadero (2021), Williams (2024). The concept draws on broader theoretical frameworks from cybernetics and systems theory, emphasizing the importance of feedback in regulating and improving systems beyond the education sector. Large feedback increments ("exploding" gradients) can cause learning failures, while small increments ("vanishing" gradients) may slow down learning. The ideal feedback (gradients) is coarse-to-fine, with large adjustments at first when the goal is far away, and smaller corrections as the target gets nearer.

**Figure 5**
*Learning Feedback Loop*




*Source*: Improving student learnability with a feedback loop (clipart from Williams, 2024).

### *Qualitative vs. Quantitative Feedback*

AI/ML methods such as the boosting introduced above and the ANNs utilize quantitative feedback in the form of loss function gradients to enable learning models to solve various prediction problems.

HL accepts both quantitative and qualitative feedback, as both are essential in education and complement each other in enhancing student performance: a) Quantitative feedback indicates what students have achieved in terms of measurable outcomes; b) Qualitative feedback helps students understand how to improve their learning strategies and processes.

Just as AI/ML, HL requires a free flow of feedback and is sensitive to feedback flow obstructions.

## Machine Learning vs. Human

Assuming that the free flow of feedback is maintained, we can analyze what factors would contribute to the success of Machine and Human Learning, respectively.

### *Machine Learning – Success Factors*

We would suggest that the success of an AI/ML is a "function" of the following factors:

$$Learning_{Success} = f(Problem\ Learnability + Cognitive\ Skills + Motivation + Other\ Factors) \tag{4}$$

Let us consider the factors one by one:

- *Problem learnability* in AI/ML is based on computational learning theory, which states that a problem is learnable if an algorithm can effectively approximate the target concept from training data (Jha, 2024; Kearns & Vazirani, 1994; Shalev-Shwartz & Ben-David, 2014; Williams, 2024). Once learnability is established, AI/ML methods like gradient boosting or ANN can transform weak learners into strong ones.
- *Motivation* is "the process whereby goal-directed activity is instigated and sustained" (Schunk et al., 2008), as it refers to the internal drive that initiates and keeps someone actively working toward a specific goal. Unlike humans, machines possess intrinsic motivation; they strictly follow their programming instructions, whereas humans may vary in their willingness to engage with the learning process.
- *Cognitive skills* in AI/ML are determined by the computational capabilities, which can easily be provided to meet the demands of popular AI/ML methods.
- *Other factors* can include the data quality and quantity, model hyperparameters, and other auxiliary implementation aspects.

Therefore, the success of machine learning is fundamentally assured once **learnability is established**, regardless of the starting point. Other factors can be managed but still need to be considered.

$$AI/ML_{Success} = f(Problem\ Learnability + Other\ Factors) \tag{5}$$

Note that prior knowledge is not one of the major factors here.

***Human Learning – Success Factors***

Achieving learning outcomes in human learning (HL) requires adequate cognitive skills and motivation. Assuming the program is learnable and instruction is appropriate, success depends on the learner's cognitive-motivational profile, which combines cognitive skills and motivational factors that influence learning and performance (Bandura, 1986; Cordeiro, 2016).

Let us take another look at the function (4), and consider the factors for HL case one by one:

- *Problem learnability* - in higher education, programs are designed to be learnable, as demonstrated by previous successful completions. Therefore, "weak" human learners can achieve learning outcomes if they have enough motivation and cognitive skills. The variation in human motivation and cognitive abilities means that while machines can reliably reach learning goals, humans need a supportive environment that fosters motivation and develops cognitive skills.
- *Motivation* - low motivation hinders the free flow of feedback, negatively impacting the “feedback receptivity” (Lipnevich & Panadero, 2021). Motivation is dynamic and changes over time, in response to situations and course content. It is the inner drive that starts and maintains goal-oriented activity. Without strong motivation, the learning process is unlikely to succeed, regardless of cognitive skills. Regular motivation checks, ideally at the start of each course, are crucial to keep learners engaged. This helps prevent instructors from wasting resources on less motivated learners.
- *Cognitive skills* - often assessed during program admission. They tend to be relatively stable and are unlikely to change significantly within a single course or program.

Therefore, once cognitive skills are confirmed, they usually do not require frequent reassessment.

- *Other factors* - such as instructional methods and presentation of the material, e.g., Anderson (2015)—are external to the learner's profile and fall clearly within the instructor's responsibility.

**Table 2**
*Aspects of HL and the ML Differences*

| Human learning (HL) | Machine learning (ML) |
|---|---|
| *Motivation* (desire/willingness) to learn is not inherent and is a major factor. | *Motivation* is not a factor. |
| *Cognitive skills* needed to acquire essential knowledge vary from person to person and are a major factor. | The machine's *cognitive skills* are not a factor given adequate computational capabilities. |
| HL (education) tasks are *learnable*; the learnability is not a factor. | ML tasks' *learnability* varies; it is generally a factor. |

$$HL_{Success} = f(Motivation + Cognitive\ Skills + Other\ Factors) \tag{6}$$

In summary, the guaranteed success of AI/ML for learnable problems and the fact that educational programs are learnable suggest that a motivated, initially "weak" human learner with cognitive skills, given proper guidance, will succeed in achieving learning outcomes in educational programs.

### *Learner Motivation Assessment*

As we observe, motivation and cognitive skills are among the main success factors of HL (6). It would be helpful to evaluate them to predict students' success. Unlike cognitive skill assessment, which can be done once per degree program, motivation is dynamic, see e.g., Eccles and Wigfield (2002), and needs to be tested more often, perhaps once per semester. A single test or interview cannot reliably measure motivation, as a "snapshot" may not accurately reflect a learner's true motivation.

A more dependable sign of motivation is how the learner responds to feedback or other communication from the instructor (see Hattie & Timperley, 2007). Active participation in feedback demonstrates a learner's dedication to the learning process. Therefore, practical methods for assessing motivation should concentrate on the learner's reaction to the instructor's communication or task.

Simple tests can gauge motivation by assessing the learner's reaction to a specific task ("goal-directed activity"), see **Table 3**. These tests focus not on knowledge but on the openness of the communication channel and the learner's response. The sequence of steps is important: a) the instructor's action (task), b) the learner's reaction, and c) the instructor's assessment of whether the reaction is adequate.

**Table 3**
*Examples of Motivation Assessment Tests*

| Sequence of Actions | Diligence Test | Attention/Collaboration Test |
|---|---|---|
| 1. Instructor's Action: | Suggest a material to read/review, software to install, etc. | Guide to formatting electronic submissions. |
| 2. Learner's Reaction: | The learner takes the requested action. | The learner implements the guidance. |
| 3. Instructor's Assessment: | Assess the thoroughness of the execution. | Assess the completeness and accuracy of the execution. |

Applying these tests early in the program helps assess the learner's motivation. Although imperfect, these tests offer insights into the learner's engagement and willingness to learn.

## HL Strategies Inspired by AI/ML

### *AdaBoost-Inspired*

As described in Chapter **AI/ML: Boosting Methods**, AdaBoost gradually improves the performance of weak learners, eventually turning them into strong learners (predictors). It does this by increasing the weight of misclassified instances, making them more influential for the next model in the sequence, and so on. HL can implement the following AdaBoost-inspired techniques, progressively filling in gaps in learners' knowledge, resulting in coherent and positive learning outcomes, as shown in **Table 4**.

**Table 4**
*HL Techniques Inspired by AdaBoost*

| Instructor actions | Learner actions | Benefits |
|---|---|---|
| Assign higher weights to significant errors, essential gaps, etc. | • Allowed to retake exams<br>• Allowed to redo assignments<br>• Allowed multiple attempts on quizzes | • Learners are assisted in recognizing their weaknesses and focusing on them in future attempts.<br>• Learners should see errors as opportunities to improve rather than fear them. |

### *GB-Inspired vs. Conventional Quantitative Feedback*

The GB-inspired approach is based on an incremental grading system. The goal is to enhance students' knowledge (learning outcomes) by the end of the program; therefore, consistently applying incremental progress is a way to reach this goal. This is exactly how AI/ML accomplishes its objectives.

*Conventional quantitative feedback* is given to a student as a grade (score). Conventional, or “fair,” grading evaluates students' work solely based on correctness, without considering their speed of progress. It ensures the same grade for equal levels of work quality. As a result, students with advanced prior knowledge are more likely to receive higher grades, while students with weaker prior knowledge, or "weak” learners, are more likely to get lower grades, regardless of their progress.

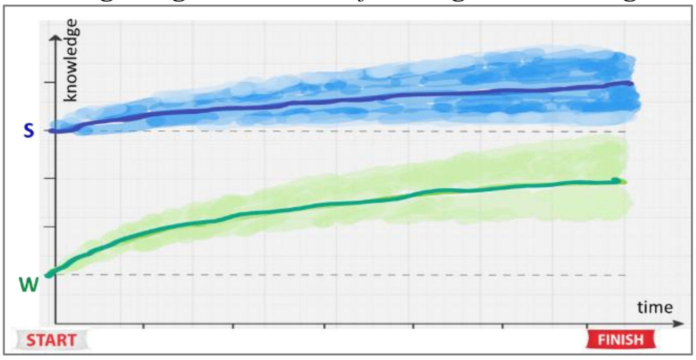
The iterative progress of initially stronger learners (**S)** and weaker ones (**W)**, with variation margins due to individual learner and instructor characteristics, curriculum, and other factors, is shown in **Figure 6**. The initial gaps in the knowledge in **Figure 6**a) and the grade in **Figure 6**b) will shrink somewhat, indicating initial faster progress when learning from a lower base; see, e.g., Fitts and Posner (1967), Anderson (1982). However, the gap will not be entirely bridged, see $\mathbf{W_{fair}}$ and $\mathbf{S_{end}}$ in **Figure 6**b).

*The GB-inspired quantitative feedback* method is based on gradient boosting principles, adjusting grades according to progress since the last milestone. This approach promotes ongoing improvement and increases motivation, especially for learners who start off weaker.

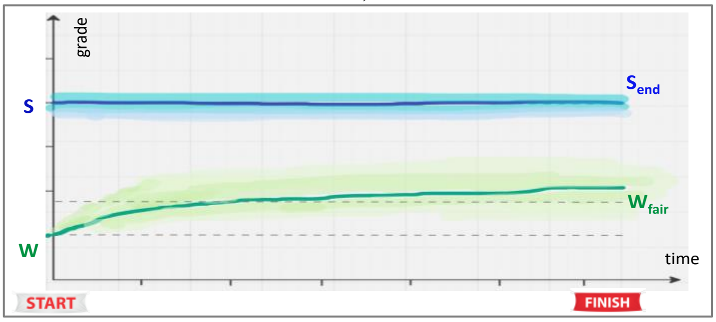
In conventional grading, students' work is evaluated based solely on solution correctness, often leading to higher grades for those with advanced prior knowledge and lower grades for initially weaker learners. The GB-inspired method adjusts grades according to progress, rewarding each iteration based on the amount of improvement made. This means that a student's grade reflects both the accuracy of their current work and their iterative progress from the last assessment, acting as a bonus. For instance, a motivated student showing significant improvement in subsequent assessments would have their grade boosted to reflect this progress, further reducing the gap (see **Figure 7**a vs. **Figure 6**a).

This approach might seem counterintuitive, as the initially weak learners could reach or even surpass those with more prior knowledge. Possible reasons for the quick progress may be related to the "clean slate" and "beginner's mind" ideas, as discussed by Locke (1689), Kalyuga et al. (2003), and Kabat-Zinn (2003).

**Figure 6**
*Learning Progress Curves of a Program Utilizing a Conventional Performance Assessment*




a)

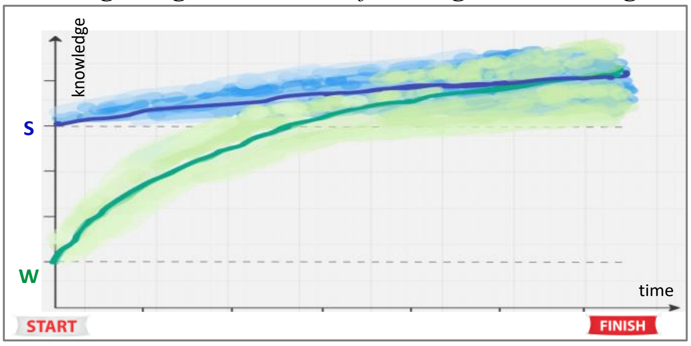



b)

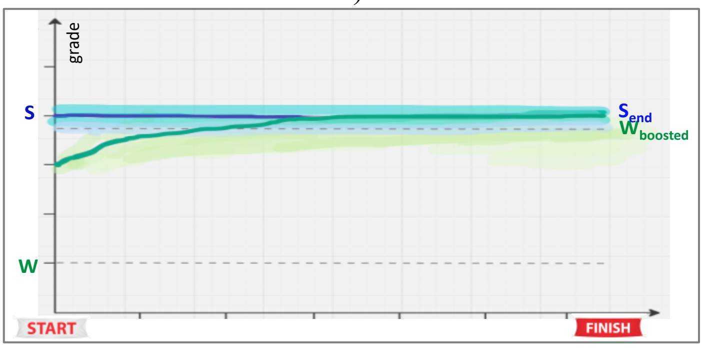
*Note*: a) Learning progress curves with variation margins for an initially stronger learner, **S**, and a weaker one, **W**, of a program utilizing a conventional performance assessment; b) Grade evolution under the "fair" grading scheme. We assume that both learners are equally capable and motivated.

Inspired by gradient boosting, the boosted grading approach adjusts grades based on the speed of progress, which can challenge the assumption that equal-quality work warrants equal grades, also known as "fair grading." However, extra credits are common in higher education, such as Skinner (1953). The class will likely see grade bonuses as justified if the grading criteria are transparent and the rapid progress bonuses are accessible to all students.

**Figure 7**
*Learning Progress Curves of a Program Utilizing a Boosted Grading*




a)




b)

*Note:* a) With the "boosted" grading adopted, a motivated **W** will likely reduce the gap faster than under the conventional grading scheme in Figure 6; b) **W's** grades will start higher, and the end grade will be close to the **S's**.

## Discussion

The study emphasizes the greater importance of motivation and cognitive skills over prior knowledge in achieving successful learning outcomes in education. AI/ML inspiration indicates that motivated learners can perform well regardless of their prior knowledge. This challenges the traditional focus on the latter and demonstrates the potential for AI-inspired assessment methods to influence education.

The analogy between weak and strong learners in AI/ML and HL (Human Learning) offers valuable insights. Boosting techniques can transform weak AI models into strong ones. Likewise, structured, iterative feedback can help initially weaker students catch up with their more knowledgeable peers, promoting ongoing improvement and fairness.

Feedback mechanisms are essential in both AI/ML and HL. Balanced feedback promotes optimal learning conditions, encouraging students to steadily advance. Inspired by AI, quantitative feedback offers students clear and actionable insights.

Boosting techniques, such as Gradient Boosting and AdaBoost, provide practical strategies for performance evaluation. By encouraging quick progress and focusing on fixing errors, these methods help students who are initially weaker improve their performance.

Motivation is essential for effective learning. Regular motivation assessments help students stay engaged and dedicated to their learning goals, fostering a supportive learning environment.

## Conclusions

This study takes inspiration from established AI techniques to enhance human learning and performance assessment. By drawing parallels between AI methods and HL processes, we propose a new approach that uses AI-inspired strategies to improve educational outcomes. Key findings from this research include:

- **From "Weak" to "Strong" Learners:** Structured feedback and iterative training can turn students with limited prior knowledge into high-achieving learners.
- **Feedback Mechanisms:** Feedback inspired by AI/ML methods, such as Gradient Boosting and AdaBoost, encourages quick progress, helping initially weaker students catch up with their peers.
- **Motivation** is crucial for effective learning, and this study emphasizes the importance of regular motivation assessments. Since motivation can vary over time, it should be reassessed periodically.
- **Practical Implications:** By adopting incremental grading and error-focused learning techniques, instructors can improve learning outcomes, helping a broader range of students, including those with limited prior knowledge, to succeed.

Integrating AI-inspired methods into education practices offers promise for improving student performance assessment and developing more effective, fair, and motivating learning environments.

## Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The Grammarly AI writing assistant was used to enhance the writing style and grammar.

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