Inverted Grading in Project-Based Learning: A Learning Path Approach for Sustainable Performance Evaluation

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Abstract

Higher education assessment is traditionally based on cumulative grading models, where students progressively build their final classification over time. However, such approaches often promote risk-averse behaviour and limit continuous improvement.

This paper proposes an inverted grading strategy integrated with learning paths within the TechTeach paradigm. In this model, students are evaluated according to the maximum expected grade of their selected path and assessed on their ability to maintain or recover their performance throughout the course. The strategy combines group and individual evaluation, enabling effective differentiation of student contributions in project-based learning environments.

The approach was validated through a case study conducted in a Web Programming course with 153 students. The results show a dynamic evolution, with an average decrease from 16.31 at the first control point to 15.34 at the second, followed by a recovery to 16.05 in the final evaluation. The overall variation (-0.26, or -1.6%) indicates that outcomes remain close to initial performance despite intermediate fluctuations. Additionally, 62% of students experienced a decrease in grade, 28% improved their performance, and 10% maintained stable results, confirming the model's ability to capture performance dynamics and support recovery.

Student feedback further reinforces the approach's applicability, with more than 80% of responses indicating acceptance of the model.

Overall, the results suggest that inverted grading offers a robust alternative to traditional cumulative models, promoting sustainable performance, accountability, and continuous engagement in higher education.

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1 Introduction

Higher education assessment is traditionally based on incremental grading models, where students progressively build their final classification through successive evaluations. This approach assumes that learning evolves linearly and that students must demonstrate increasing levels of knowledge over time. However, in practice, this model often promotes conservative behaviour, in which students aim to meet minimum requirements rather than pursue excellence. As a result, risk-taking, continuous improvement, and recovery from mistakes are frequently limited.

From a pedagogical perspective, this raises an important question: should students always start from zero and prove their value, or should they be challenged to maintain a predefined level of excellence? In real-world environments, professionals are expected to sustain performance standards rather than gradually achieve them. Therefore, assessment models should reflect this dynamic behaviour and encourage responsibility, consistency, and effort over time.

Based on these observations, this paper introduces an inverted grading strategy within the TechTeach paradigm. Instead of starting from a minimum grade and progressing upward, students begin with a maximum expected grade. They are evaluated based on their ability to maintain or recover that level throughout the course. This approach shifts the focus from acquiring grades to sustaining performance, promoting accountability and continuous engagement.

The proposed strategy is integrated with learning paths and project-based learning, extending TechTeach [15] and previous work on personalised education [17]. It introduces distinct evaluation mechanisms for group and individual performance, ensuring that collaboration does not mask individual effort. Project outcomes define group grades, while individual grades are adjusted through peer evaluation and gamification mechanisms, such as card systems.

To validate the approach, a case study was conducted in the Web Programming course at the University of Minho, involving more than 150 students. The evaluation experiment was applied to group projects. It included two control points and a final presentation, allowing the analysis of grade evolution, recovery behaviour, and alignment between expected and achieved results across different learning paths.

This paper is structured as follows. Section 2 presents the background and related work. Section 3 describes the material and methods used in the study. Section 4 introduces the inverted grading model and its rules. Section 5 presents the case study and implementation details. Finally, Section 6 concludes the paper and outlines future work.

2 Background

This section presents the main topics of the work and reviews related work.

2.1 Assessment Models in Higher Education

Assessment in higher education plays a central role in measuring students' knowledge, skills, and competencies. Traditionally, evaluation models are based on cumulative grading approaches, in which students progressively build their final classification across multiple assessment moments, such as assignments, tests, and projects. These models assume a linear evolution of learning and are widely adopted due to their simplicity and compatibility with standard curricula structures [2].

Several alternative assessment strategies have been proposed to address the limitations of traditional grading models. Mastery learning approaches focus on ensuring that students achieve a predefined level of competence before progressing, allow multiple attempts, and emphasise learning over performance [4]. Similarly, standards-based grading evaluates students according to clearly defined learning outcomes, promoting consistency and transparency in assessment [12]. These approaches shift the focus from point accumulation to knowledge acquisition.

Other models, such as contract grading and specifications grading, introduce a negotiation component in which students define their expected level of achievement and must meet specific criteria to obtain a target grade [14]. These strategies are particularly relevant in project-based learning contexts, as they align expectations with student goals and encourage responsibility in the learning process.

In parallel, formative assessment models emphasise continuous feedback and iterative improvement, allowing students to adjust their performance throughout the learning process [3]. More recently, gamification mechanisms have been integrated into assessment to increase

engagement and provide dynamic feedback through points, levels, and rewards [8]. These approaches have demonstrated positive effects on motivation and participation, especially in large classes.

Despite these advances, most existing models rely on additive or progressive grading logic, in which students start at a minimum value and improve their classification over time. Few approaches consider reversing this perspective by defining a maximum expected performance from the outset and evaluating students based on their ability to sustain or recover that level.

This gap motivates the proposed inverted grading strategy presented in this paper, which extends existing assessment approaches by introducing a dynamic model in which grades may decrease or be recovered based on students' performance over time.

2.2 Learning Paths and Outcomes

Pedagogical innovation is essential to teaching success, and learning paths are a simple way of personalising learning. Personalised learning is an alternative to the "one-size-fits-all" model and refers to approaches that offer multiple learning paths that account for individual differences in learning preferences, goals, abilities, and background knowledge [5, 7]. A learning path, which embodies curriculum design, comprises a sequence of structured learning activities to help students achieve predefined learning objectives [6, 13]. These paths must align with student-centred learning outcomes that describe the measurable skills, knowledge, or values students should demonstrate upon completing a course [19]. The differentiated learning path strategy also aligns with personalised learning approaches, in which students select challenge levels based on their goals and capabilities.

In previous work, a two-path strategy was proposed within the TechTeach paradigm to address the diversity of student goals in higher education [17]. The first path was designed for students aiming to ensure the minimum knowledge required for the subject, while the second was designed for those seeking a deeper, more specialised understanding. The results showed that students valued the ability to choose their trajectory to align with their goals, while maintaining learning outcomes and academic rigour.

2.3 Alternative Grading and Incentive-Based Assessment

Assessment in higher education traditionally relies on cumulative, incremental grading models, in which students progressively accumulate points through successive assignments and evaluations. Although widely adopted, such approaches may unintentionally encourage risk-averse behaviour, leading students to focus on securing minimum acceptable outcomes rather than pursuing excellence, sustained improvement, or recovery after weak performance. This limitation is particularly relevant in project-based learning environments, where performance depends not only on technical achievement but also on consistency, engagement, collaboration, and the capacity to evolve over time.

Assessment design itself has been shown to influence student motivation and behavioural strategies. Docan analysed positive and negative incentive structures in grading, including models in which students either accumulate points progressively or start with a maximum score that decreases with performance, thereby highlighting the motivational implications of grading mechanics [9]. Similarly, MacDermott demonstrated that grading policies can shape strategic student behaviour, reinforcing the idea that assessment systems influence not only outcomes but also students' engagement with learning activities [11].

Building on this perspective, this work explores an alternative assessment logic through an inverted grading model, in which students start from the maximum grade associated with their selected learning path and are evaluated on their ability to maintain or recover performance throughout the project lifecycle. Rather than rewarding only upward accumulation, the model emphasises performance sustainability, accountability, and continuous effort.

This perspective is also aligned with real-world professional contexts, where individuals are typically expected to maintain quality standards over time and respond effectively to performance deviations rather than accumulate symbolic rewards.

Furthermore, the proposed model integrates personalised learning through differentiated learning paths with distinct performance ceilings, allowing students to self-regulate their level of challenge and ambition. Combined with the separation of group and individual evaluation, this ensures that final outcomes reflect both collective project success and individual contribution.

2.4 TechTeach and Gamification

In 2020, Filipe Portela introduced TechTeach, a gamified approach that engages students in the classroom through active methodologies, project-based learning, and digital support tools [15]. Since then, the paradigm has evolved with new strategies, including gamified assessment mechanisms and individual validation models [16]. These approaches have shown that gamification can play an important role not only in motivation but also in performance monitoring, encouraging participation and promoting fairer evaluation processes.

In this context, mechanisms such as peer evaluation, quizzes, and card systems are relevant because they provide continuous signals of student performance and commitment. Recent work has also shown the value of combining multiple sources of evidence in assessment processes, including behavioural indicators, peer feedback, and project participation [18]. Therefore, the inverted grading strategy presented in this paper is framed within TechTeach and extends its logic by introducing a dynamic model in which grades may decrease or be recovered during the project, depending on the work performed.

3 Material and Methods

This work is based on the case study method, which enables the exploration of a specific occurrence or phenomenon [20]. The process of conducting a case study typically unfolds through several stages, including the development of the design, data collection, analysis of findings, and interpretation of results [1]. The specific phases and activities involved in this case study are as follows:

- Design:
  - Understand students' motivation and goals regarding project-based evaluation
  - Study alternative evaluation models to improve students' engagement and performance
  - Design an inverted grading strategy aligned with learning paths
  - Define evaluation moments (control points and final presentation)
- Implementation:
  - Define the rules and evaluation logic of the inverted grading model
  - Adapt the subject evaluation plan to include the proposed strategy
  - Integrate group and individual evaluation mechanisms
  - Apply the strategy to a real project-based learning context

- Analysis:
  - Compare expected grades with achieved results across evaluation moments
  - Analyse grade evolution between control points and final presentation
  - Evaluate differences between learning paths and their outcomes
- Interpretation:
  - Analyse the impact of the inverted grading strategy on student performance
  - Evaluate how grade variation reflects student effort over time
  - Explore the implications of this model in higher education assessment

The application of the case study methodology is justified because it is necessary to evaluate a new assessment strategy in a real-world educational context while maintaining the subject's learning objectives. This methodology has demonstrated its applicability to research in real-world settings [10], as it allows professors to observe student behaviour over time and relate it to performance outcomes across different evaluation moments.

Regarding the tools, Kahoot was used to collect students' feedback at different stages of the subject and to support continuous evaluation through quizzes [16].

4 Inverted Grading Model

This section presents the inverted grading strategy proposed for project-based learning within the TechTeach paradigm. The proposed strategy specifically employs a maximum-reference inverted grading model, in which evaluation begins at the highest achievable grade defined by the selected learning path. Alternative inverted variants could be explored, but they are outside the scope of this work.

4.1 Concept

The inverted grading model is based on a reversed evaluation logic, in which students do not start at a minimum grade and progress upward. Instead, they begin with the maximum expected grade for the selected learning path and are evaluated based on their ability to maintain or improve that level over time.

In this model, assessment is dynamic and iterative. At each evaluation point, students' performance is analysed against the expected quality level. If the work meets the expected standards, the grade is maintained. Otherwise, the grade may decrease. Students may improve their grades in subsequent evaluations by demonstrating higher performance and effort.

This approach shifts the focus from acquiring grades to sustaining performance, encouraging students to maintain consistent effort throughout the project lifecycle.

4.2 Evaluation Structure

The evaluation process is organised into three main moments:

- Control Point 1 (CP1)
- Control Point 2 (CP2)
- Final Presentation (FA)

At CP1, the evaluation is performed at the group level and defines the effective starting point of the inverted grading trajectory. Although students are conceptually evaluated against the maximum grade of their selected path, CP1 establishes the first real value based on the quality of the work developed.

From CP2 onward, the evaluation is performed individually and may include decimal values. The grade at each time step is determined by the previous one, reflecting the evolution of performance over time.

4.3 Grading Logic

The grading logic follows three main principles:

1. **Maximum Reference**: Each learning path defines the maximum achievable grade (e.g., 14 or 20).
2. **Dynamic Adjustment**: Grades may decrease when performance does not meet expectations.
3. **Performance Improvement**: Students may improve their grades in subsequent evaluations.

This approach creates a non-linear grading trajectory, where grades evolve according to performance consistency rather than cumulative accumulation.

4.4 Group and Individual Evaluation

Initially, evaluation is group-based (CP1), where all members share the same grade.

From CP2 onward, individual evaluation is introduced. Each student's grade may differ from the group average, reflecting contributions, effort, and performance, supported by peer evaluation and gamification mechanisms.

4.5 Grade Evolution

Examples of grade trajectories include:

- Stable performance: $20 \rightarrow 20 \rightarrow 20$
- Slight degradation: $20 \rightarrow 19.50 \rightarrow 18.35$
- Improvement: $20 \rightarrow 19.50 \rightarrow 20$
- Low performance leading to failure: $13 \rightarrow 10 \rightarrow \text{R}$

4.6 Integration with Learning Paths

Each learning path defines the maximum achievable grade:

- Traditional path: 14
- Expert path: 20

Although students are conceptually evaluated against this maximum, CP1 defines the effective starting point of the inverted grading trajectory.

5 Case Study

This study was conducted in the Web Programming course at the University of Minho and involved 153 students organised into project groups.

Students selected either the Traditional or Expert learning path, which defines the maximum achievable grade. The inverted grading strategy was applied to project evaluation at three moments: CP1, CP2, and final presentation (FA).

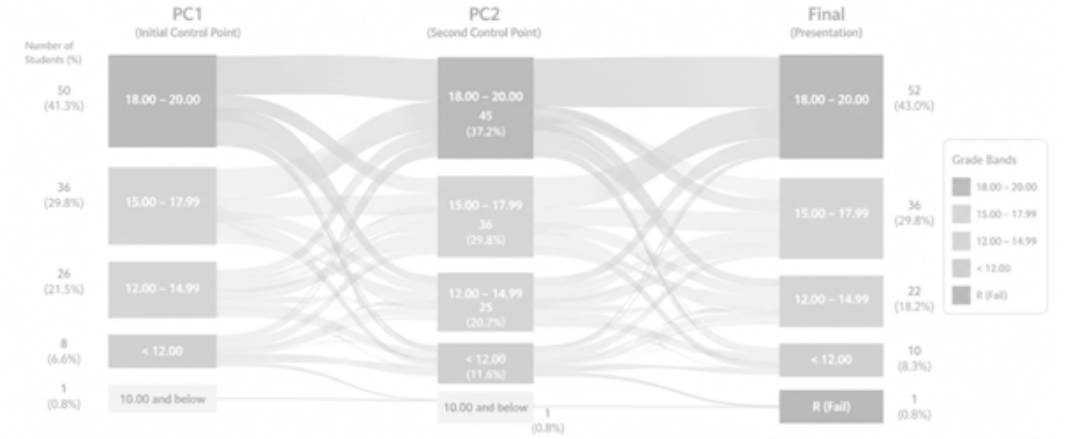

Figure 1 Student grade flow across the three evaluation moments (CP1, CP2, and Final), illustrating transitions between grade bands under the inverted grading strategy.

At CP1, evaluation is performed at the group level and defines the starting point of the grading trajectory. From CP2 onward, evaluation becomes individual, enabling differentiation based on contribution, effort, and performance. Peer evaluation, non-work indicators, and gamification mechanisms support this process.

The collected dataset allows analysis of grade evolution, individual differentiation, and the overall impact of the inverted grading strategy.

5.1 Quantitative Analysis

The results show a consistent pattern of grade evolution throughout the evaluation process. The average grade decreased from 16.31 at CP1 to 15.34 at CP2, then recovered to 16.05 in the final evaluation. It corresponds to an overall variation of -0.26 (-1.6%), indicating that, despite intermediate fluctuations, outcomes remain close to the initial performance level.

Figure 1 illustrates the flow of students across grade bands throughout the three evaluation moments. The visual representation highlights the model's dynamic nature, showing both degradation and recovery paths.

The distribution of trajectories confirms this behaviour. Approximately 62% of students experienced a decrease in their grades at some point, 28% showed improvement between evaluations, and 10% maintained stable performance. These results show that the model effectively captures performance variation and supports both penalisation and recovery.

The median final grade (approximately 16.50) is slightly higher than the average (16.05), indicating a concentration of students in the upper-middle performance range. The standard deviation (approximately 1.9) reflects moderate variability, confirming that the model differentiates performance without introducing excessive dispersion.

Only a small number of students (0.65%) were classified as failing, demonstrating that the model maintains performance standards while still allowing failure in cases of insufficient engagement.

Table 1 summarises the main quantitative indicators obtained from the dataset.

Table 1 Quantitative Results of the Inverted Grading Strategy.

Metric	Value
Number of students	153
Average grade (CP1)	16.31
Average grade (CP2)	15.34
Average final grade	16.05
Average variation (CP1 → Final)	-0.26
Relative variation	-1.6%
Median final grade	≈ 16.50
Highest final grade	20.00
Lowest final grade	0.00 (Fail)
Standard deviation (Final)	≈ 1.9
Students with grade decrease (%)	62%
Students with improvement (%)	28%
Students with stable grades (%)	10%
Students with fail result (%)	0.65%

5.2 Performance Dynamics

The transition from group-based evaluation at CP1 to individual evaluation at CP2 is critical in shaping the results. While initial grades reflect group performance, subsequent divergence captures individual effort and contribution, as observed in both Figure 1 and Table 1.

The observed decrease in grades for most students is expected under the inverted grading logic, in which evaluation starts from a maximum reference point. Maintaining high performance requires consistency, and deviations result in grade reductions. However, the recovery observed in 28% of students confirms that the model supports improvement and rewards sustained effort.

Despite these fluctuations, the limited overall variation (-0.26) indicates that the model stabilises performance over time, with students converging toward a consistent final level.

5.3 Interpretation of Results

From an analytical perspective, the results demonstrate that the inverted grading strategy introduces a controlled level of variability while preserving overall performance stability. This balance ensures both fairness and sensitivity in evaluation.

The model effectively differentiates individual contributions, promotes continuous engagement, and allows recovery from performance drops. At the same time, it avoids grade inflation, as evidenced by the presence of fail cases and the controlled distribution of final grades.

Overall, the results confirm that the inverted grading approach provides a realistic representation of student performance, aligning evaluation with effort, consistency, and progression throughout the project lifecycle.

5.4 Student Evaluation of the Model

To complement the quantitative analysis, students evaluated both the learning-path mechanism and the inverted grading strategy via anonymous polls.

The learning path mechanism received a very positive evaluation, with most responses concentrated at the highest values. A total of 32 students assigned the maximum score, and 35 rated it as excellent, whereas only 3 rated it below 3. This distribution indicates strong acceptance and confirms the relevance of differentiated learning paths.

The inverted grading mechanism was also positively evaluated. In grades 1-5, a total of 34 students explicitly approved the model (5), while 42 agreed with minor adjustments (3), and only 7 expressed disagreement (1 or 2). Overall, more than 80% of responses indicate acceptance or strong acceptance.

These results reinforce the perception that the model is fair, transparent, and aligned with student effort, supporting its applicability in real educational contexts.

5.5 Discussion

The results demonstrate that the inverted grading strategy effectively shifts evaluation from cumulative accumulation to performance sustainability. Rather than rewarding isolated improvements, the model evaluates students based on their ability to maintain a consistent level of performance over time. This analysis is supported by the limited overall variation between the first and final evaluation moments (-0.26, corresponding to -1.6%), indicating that outcomes remain close to the initial performance despite intermediate fluctuations.

The observed decrease in grade for the majority of students (62%) is inherent to the model rather than a limitation. Since evaluation starts from a maximum reference point, any deviation from the expected level is reflected as a reduction in the score. This behaviour reflects a realistic performance scenario in which maintaining high standards is inherently challenging. At the same time, the presence of improvement cases (28%) demonstrates that the model supports recovery and rewards sustained effort, allowing students to regain performance after temporary drops.

The differentiation observed after CP2 confirms the effectiveness of separating group and individual evaluation. While CP1 reflects group performance, subsequent divergence captures individual contribution. It is reinforced by the observed variability (standard deviation of approximately 1.9), indicating that the model is sensitive to individual differences without exhibiting excessive dispersion.

Furthermore, the distribution of final grades, with a median of approximately 16.50 and an average of 16.05, suggests a concentration of students in the upper-middle performance range. It indicates that the model maintains overall performance stability while still allowing differentiation. The presence of fail cases (0.65%) further confirms that the model avoids grade inflation and preserves minimum performance standards.

From a pedagogical perspective, the combination of quantitative results and student feedback reinforces the approach's validity. With more than 80% of students accepting the model, the results indicate that the strategy is not only effective but also perceived as fair, transparent, and aligned with individual effort.

Overall, the results support the use of inverted grading as a promising alternative to traditional evaluation models. The strategy promotes continuous engagement, enables performance recovery, and ensures meaningful differentiation, making it particularly suitable for project-based learning environments where sustained effort and individual contribution are critical.

6 Conclusion

This paper introduced an inverted grading strategy integrated with learning paths and project-based learning within the TechTeach paradigm. The proposed model shifts the traditional evaluation perspective from cumulative grade acquisition to sustained performance assessment, in which students are evaluated on their ability to maintain or recover expected performance levels over time. This approach aims to reflect better performance-oriented contexts, where continuity, accountability, and consistent delivery are often valued over isolated achievements.

The case study, conducted with 153 students in a Web Programming course, demonstrated that the model supports a dynamic and structured evaluation process. Quantitative results showed that average grades decreased from 16.31 at the first control point to 15.34 at the second, then recovered to 16.05 in the final evaluation. The limited overall variation (-0.26, corresponding to -1.6%) suggests that, despite intermediate fluctuations, outcomes remain relatively stable.

Further analysis revealed that 62% of students experienced a temporary decrease in performance, 28% demonstrated measurable recovery between evaluation moments, and 10% maintained stable trajectories throughout the process. These findings indicate that the proposed strategy effectively captures performance dynamics over time, supporting both penalisation and recovery mechanisms rather than relying exclusively on cumulative accumulation.

The transition from group-based to individual evaluation proved particularly relevant in differentiating student contributions. Students in the same project group achieved distinct outcomes, as evidenced by peer evaluations and gamification, thereby reinforcing fairness and accountability. The observed variability (standard deviation of approximately 1.9) confirms that the model differentiates performance without introducing excessive dispersion. Additionally, the median final grade (approximately 16.50) and the low fail rate (0.65%) indicate that the model preserves performance stability while maintaining minimum academic standards.

From a pedagogical perspective, students' perceptions further reinforce the approach's applicability, with more than 80% of respondents expressing acceptance of the model. It suggests that the strategy is generally perceived as fair, transparent, and aligned with individual effort.

Nevertheless, several limitations should be acknowledged. First, the absence of a direct control group using a traditional cumulative grading model prevents a rigorous comparative evaluation of effectiveness. As the strategy was applied to the entire cohort, the analysis focuses on internal behavioural dynamics rather than comparative performance outcomes. Second, starting from a maximum reference grade may introduce psychological pressure for some students, particularly those who perceive evaluation as primarily centred on identifying deficiencies rather than recognising achievements. Third, the learning path mechanism may encourage strategic behaviour, where some students select lower-complexity paths to reduce perceived risk, potentially limiting ambition or recovery potential. Finally, the study was conducted in a project-based programming context, which may restrict the generalisability of the findings to other educational domains.

Overall, the results suggest that inverted grading constitutes a promising alternative to traditional cumulative assessment models, particularly in project-based learning environments where sustained effort, accountability, and individual contribution are critical. Future work should focus on controlled comparative studies with traditional grading models, deeper analysis of psychological and motivational impacts, refinement of evaluation indicators, and

validation across different disciplines and educational settings.

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