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Every iota counts - Using Predictive Analytics to Improve Student Success in Large Courses

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Every *iota* counts – Using Predictive Analytics to Improve Student Success in Large Courses

Abstract

Students at large public universities often struggle to track their academic progress due to diverse backgrounds, varying levels of preparation, and competing responsibilities, which can lead to poor performance, course withdrawal, or failure. To address this challenge, we present iota, a cloud-based platform for automated grade calculation, performance prediction, and communication that provides students with real-time visibility into their academic standing through optimistic and realistic grade forecasts. iota promotes student self-awareness and ownership of learning while enabling instructors to identify at-risk students, diagnose assessment-level difficulties, and implement timely, data-driven interventions. The system has been deployed across multiple lower- and upper-division courses, including programming, computer architecture, data structures, and algorithms, at several U.S. universities, and has been used by over 1K students. We analyze anonymized student performance data and feedback to demonstrate the potential value of iota in supporting academic planning, evidence-based instructional design, and equitable student support, while reducing grading complexity and freeing instructors to focus on pedagogy, mentorship, research, and service.

1. Introduction

Large public universities serve increasingly diverse student populations with wide variations in academic preparation, socioeconomic background, and external responsibilities. While this diversity enriches the learning environment, it also introduces challenges in student persistence, performance monitoring, and timely intervention. Prior studies have shown that students who lack clear awareness of their academic standing are more likely to disengage, withdraw, or fail courses, particularly in large, assessment-intensive classes such as computing and engineering [1], [2]. These challenges contribute to equity gaps and place additional demands on instructors, who must balance instructional quality, grading complexity, and student support at scale.

Assessment transparency and timely feedback are widely recognized as critical factors in student success. Frequent, formative assessment and actionable feedback have been shown to improve learning outcomes, retention, and self-regulated learning behaviors [3], [4]. However, in large-enrollment courses, manually aggregating grades, identifying at-risk students, and communicating personalized guidance can be time-consuming and error-prone. As a result, instructors often rely on coarse indicators such as midterm grades, which may arrive too late for effective intervention.

Learning analytics and educational data mining have emerged as promising approaches for addressing these challenges by leveraging student performance data to support prediction, early warning, and instructional decision-making [5],[6]. Several systems have explored grade prediction and risk detection using historical or real-time data [7], [8]. However, many existing tools either lack transparency for students, require complex setup, or do not integrate naturally with instructors' grading workflows. Moreover, few platforms explicitly support both student-facing planning (e.g., "what-if" scenarios) and instructor-facing adaptive grading and advising in a unified framework.

In this paper, we present *iota* [9], a cloud-based platform for automated grade calculation, predictive analytics, and personalized communication designed to support both students and instructors throughout the semester. *iota* provides students with real-time visibility into their performance through optimistic and realistic grade projections, enabling informed academic planning and self-regulated learning. For instructors, iota reduces grading complexity, supports outcome-based assessment reporting, and enables early identification of at-risk students for timely, data-driven intervention.

We begin first by presenting *iota* in detail in section 2 followed by analyzing longitudinal student performance data and feedback in section 3 to demonstrate how iota improves predictive accuracy over time, supports adaptive instructional and grading strategies, and aligns with accreditation and continuous-improvement requirements. Our results suggest that integrating transparent grade prediction and analytics into routine course workflows can enhance student decision-making, promote equitable support, and reduce instructor workload without altering existing assessment structures.

2. *iota* – An easy grade compilation, monitoring and prediction tool

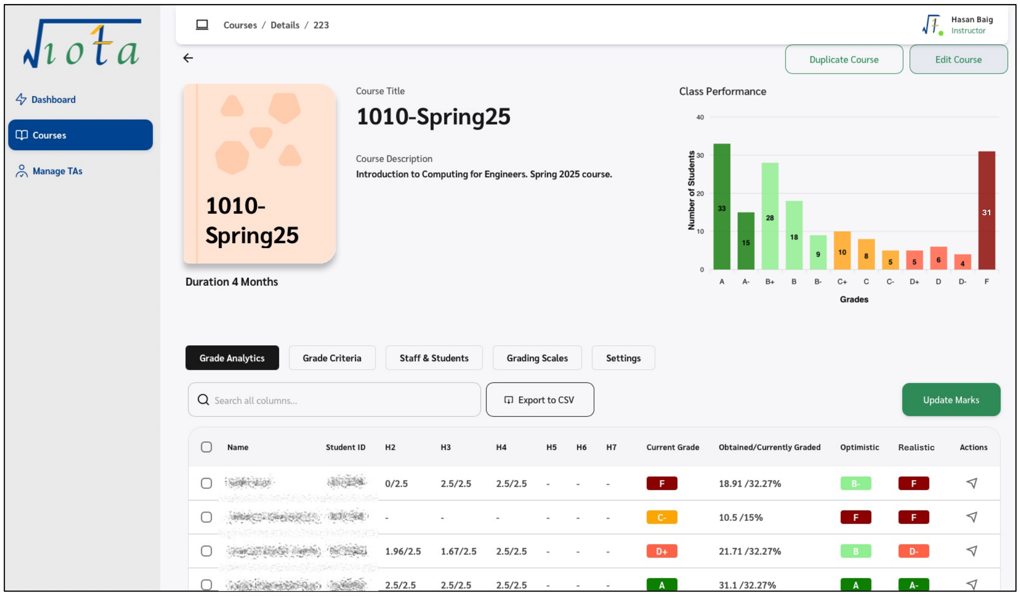
This section presents iota in detail and discusses its capabilities that benefit both students and instructors. iota is a flexible, course-agnostic platform that can be deployed across disciplines and supports a wide range of assessment and grading schemes.

Figure 1(a) shows the instructor dashboard summarizing overall class performance at a given point in the semester. The iota system provides both optimistic and realistic performance predictions and identifies students at risk of failure, enabling timely instructional intervention and informed academic guidance. This high-level overview also allows instructors to monitor longitudinal performance trends and assess the effectiveness of instructional strategies.

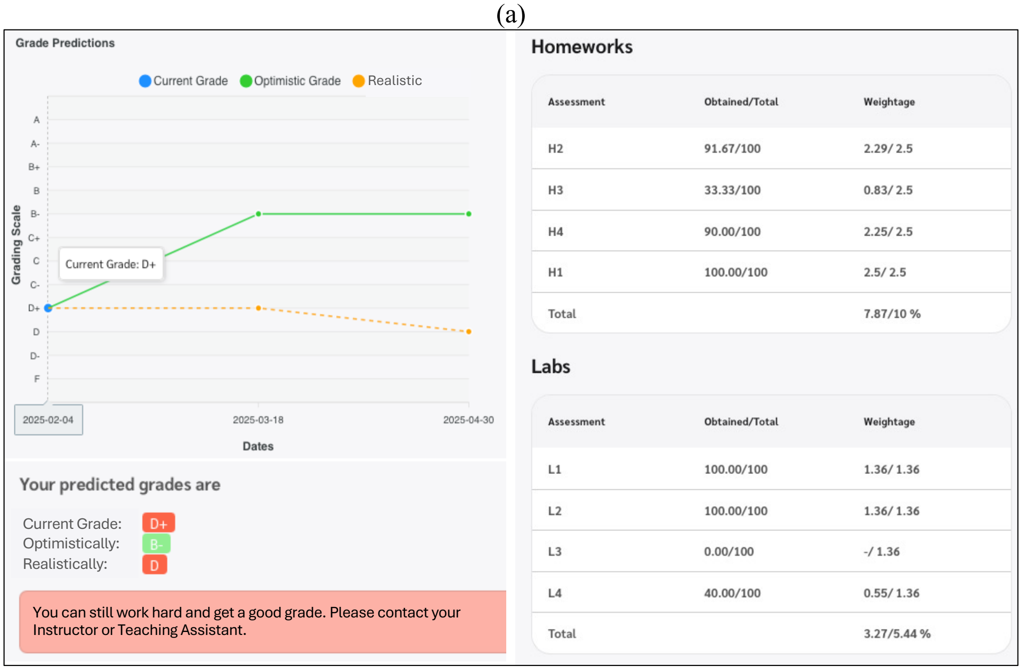
Similarly, Figure 1(b) shows selected views from the student interface, which highlight each student's projected grade trajectory, a detailed progress report across assessments, and a brief personalized message tailored to their current performance. This approach not only increases students' awareness of their academic standing but also provides encouragement by reinforcing that improved effort and engagement can positively influence their final outcomes.

2.1. Easy grade compilation

iota significantly reduces instructors' effort in periodically compiling students' progress, whether in terms of grades or GPA. As shown in Figure 1(a), the instructor interface provides multiple tabs for configuring grading criteria, managing enrolled students, TAs, and other course staff. Through the settings tab, instructors can specify assessment drop policies, control grade visibility for students, and define prediction thresholds (see Section 3.4), among other options.



(a)



(b)

Figure 1. Selected screenshots of iota web tool. (a) Class performance graph under Instructor's view at a certain time during the semester. (b) Selected student's views showing their possible predictions by the end of semester.

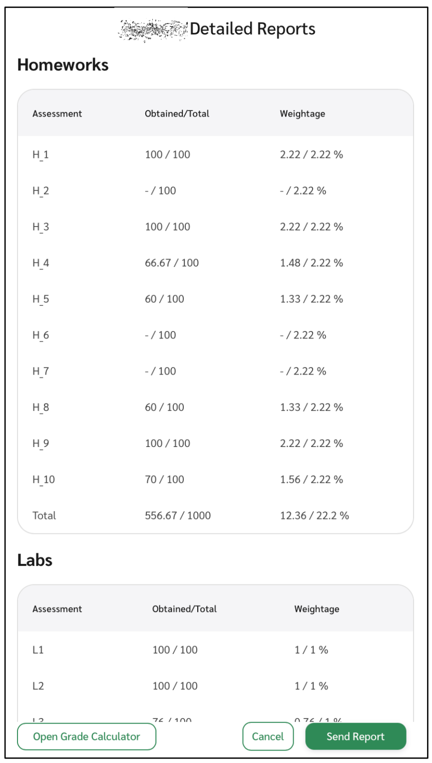
In addition to supporting arbitrary grading schemes defined by instructors, iota includes built-in support for processing CSV grade sheets generated by zyBooks [10]. zyBooks is an automated grading platform commonly used for programming-related assessments and produces fine-grained exercise-level scores. For example, a single lab may consist of multiple exercises, each graded independently, which must then be scaled to match the weight of the corresponding assessment category. Across weekly labs and homework assignments, this results in highly data-intensive grade sheets, often containing thousands of columns, making manual aggregation time-consuming and error-prone. iota seamlessly processes such large-scale zyBooks datasets and accurately computes cumulative scores across assessment categories.

2.2. Identifying Students At-risk of Failure

The grade sheet in Figure 1(a) highlights students currently at risk of failing, along with their optimistic and realistic grade predictions. Students whose optimistic prediction is an F can be quickly identified, enabling timely instructor intervention. This feature is especially valuable in large classes, where monitoring individual progress is challenging. iota allows instructors to efficiently review all students' performance and pinpoint those at risk of failing the course.

2.3. Efficient communication and advising

iota enables instructors to communicate students' personalized progress at scale. Each student receives a detailed report of their performance at any point in the course. Instructors can also access and send reports to individual students by clicking the arrow next to each student's name (Figure 1(a)). This capability is particularly useful during advising sessions, allowing instructors to quickly review a student's detailed progress.


Detailed Reports

Homeworks

Assessment	Obtained/Total	Weightage
H_1	100 / 100	2.22 / 2.22 %
H_2	- / 100	- / 2.22 %
H_3	100 / 100	2.22 / 2.22 %
H_4	66.67 / 100	1.48 / 2.22 %
H_5	60 / 100	1.33 / 2.22 %
H_6	- / 100	- / 2.22 %
H_7	- / 100	- / 2.22 %
H_8	60 / 100	1.33 / 2.22 %
H_9	100 / 100	2.22 / 2.22 %
H_10	70 / 100	1.56 / 2.22 %
Total	556.67 / 1000	12.36 / 22.2 %

Labs

Assessment	Obtained/Total	Weightage
L1	100 / 100	1 / 1 %
L2	100 / 100	1 / 1 %

Figure 2. Sample student's report, with detailed grading data, that can be sent to the student individually.

Figure 2 shows an example report, where instructors can immediately identify, among other assessment categories, that the student missed Homework 2, 6, and 7, and did not achieve full marks on several other assignments, potentially impacting their overall grade. Instructors can also access the grade calculator (see Section 2.6) to provide targeted guidance, helping students prioritize and focus on upcoming assessments.

2.4. Data-driven Adaption of Instruction and Grading

A bird's-eye view of overall class performance allows instructors to adjust their teaching strategies based on collective student progress. This is particularly important when a course undergoes significant redesign, as instructors need to evaluate how students are responding to the changes. iota has proven valuable in supporting such decisions, especially for courses experiencing major curriculum revamps (see Section 3.2).

2.5. Enhancing Accreditation Compliance and Teaching Effectiveness

iota supports accreditation and enhances student evaluations of teaching by providing detailed, outcome-linked performance data. For ABET and similar accreditation requirements, instructors must report how many students meet expectations, fall below expectations, or exceed expectations; iota facilitates this by automatically categorizing student performance across assessments and providing timely analytics. Students who are failing the course are identified early, allowing instructors to provide guidance so they can make informed decisions before critical deadlines, such as dropping the course to avoid an F on their transcript. This not only benefits students academically but also help preserve fair instructor evaluations, as early advising also allows students to make informed decisions about course continuation prior to course evaluation periods.

This supports equitable student outcomes by ensuring that end-of-semester evaluations reflect the experiences of students who remained actively engaged throughout the course. At the same time, iota enables instructors to adjust teaching and grading strategies based on class-wide trends and provides personalized reports that increase transparency and student engagement, demonstrating instructional effectiveness while satisfying accreditation evidence requirements.

2.6. What-if Grade Calculator

iota provides a what-if grade calculator that allows students to input hypothetical scores for upcoming assessments to determine what is required to achieve a desired final grade. As shown in Fig. 3, students can modify only future assessment scores, while completed assessments are locked to preserve grading integrity. Figure 3 also illustrates the end-of-semester view of the grade calculator, where all assessments have been completed and are therefore locked.

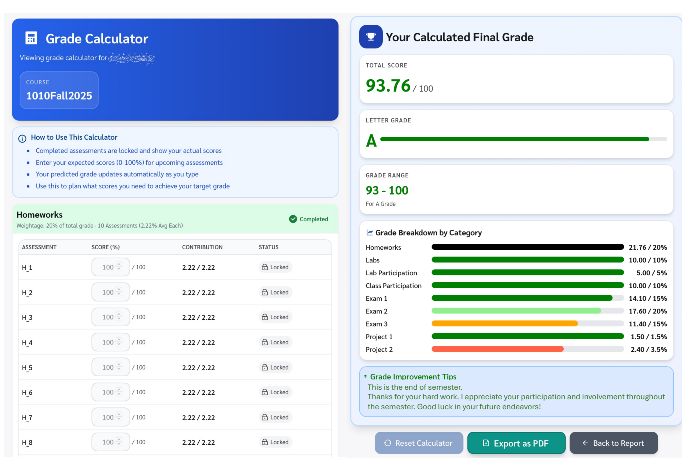


Figure 3. Student what-if grade calculator, showing the screenshot taken at the end of semester.

3. Methodology and Results

iota has been deployed across multiple courses with diverse grading criteria and class sizes ranging from 47 to over 180 students. In this paper, we present an in-depth retrospective analysis of a single representative introductory programming course taught in Fall 2025. This course was selected as a case study because it underwent a major curricular redesign to incorporate the effective use of generative AI in an introductory-level programming context, thereby providing a meaningful case study of how iota supported us, as instructors, during substantial course transformations.

All data were analyzed after course grades were finalized and were fully de-identified prior to analysis. No personally identifiable student information was used in this study.

3.1. The Course Grading Criteria

It is first necessary to describe the course grading criteria, which are summarized in Table I.

Table I: Course assessments criteria.

Homework *(one lowest to drop)*	20%
Lab	10%
Class Participation	10%
Lab Participation	5%
Final Project	5%
Exams	50%

Due to high course enrollment, hands-on programming assessments, including homework and laboratory exercises, were automatically graded using the zyBooks platform. The course was redesigned using a project-based learning model, in which students completed weekly projects that contributed to 10% of the course grade through evaluated class participation. Laboratory participation was similarly assessed based on active engagement during lab sessions.

Students completed a cumulative final project built incrementally upon their weekly project work throughout the semester. Conceptual understanding and code-writing skills were assessed through paper-based examinations designed to rigorously evaluate foundational knowledge and program-structuring ability. A total of three exams were administered at approximately one-month intervals; the first and final exams each accounted for 15% of the final grade, while the midterm exam accounted for 20%. Rather than applying grade curving, the course policy emphasized providing opportunities for students to earn bonus points as a mechanism for performance recovery.

iota was updated continuously with weekly homework and laboratory data throughout the semester. However, this paper reports prediction results at four key points in time following major assessments, such as exams and projects, and prior to the final Exam 3, after which grade prediction was no longer necessary.

3.2. Adaptive Evaluations Using *iota* Grade Distributions

As discussed earlier, iota enables instructors to make adaptive adjustments to grading and instructional strategies based on overall class performance. Figure 4 presents class-wide performance distributions at four points in time, culminating in the final course outcomes. Figure 4(a) shows class performance after Exam 1 and the completion of seven laboratory and seven homework assessments, captured immediately prior to Exam 2, where 31 students were identified as failing the course. Figure 4(b) illustrates the distribution following Exam 2, after which the number of students expected to fail increased, reflecting the higher weight (20%) of this exam relative to the others.

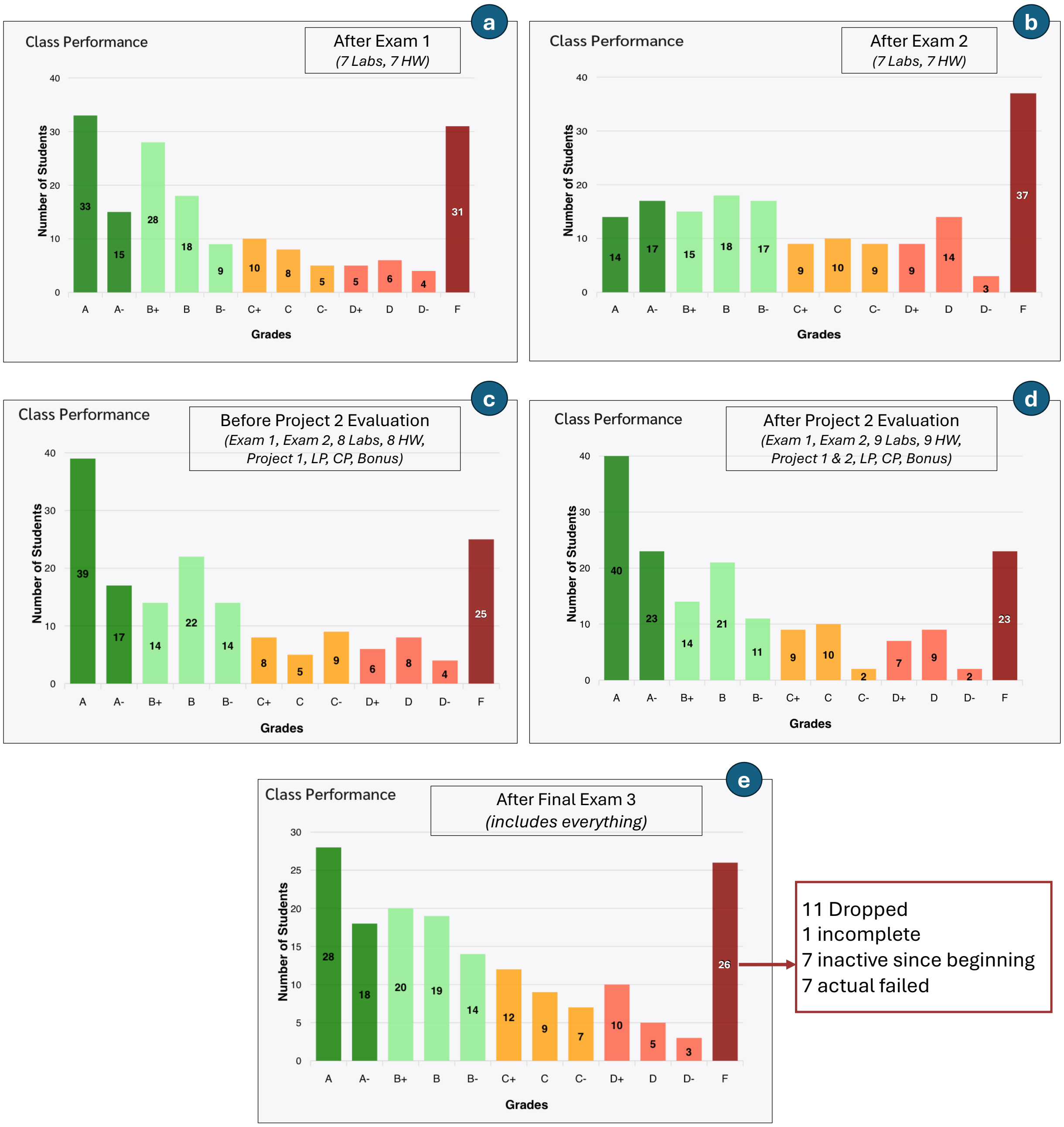


Figure 4. iota generated grade distribution and student outcomes across the semester.

Rather than curving final grades, the course policy emphasized providing structured in-class learning opportunities through which students could earn bonus points and recover from early performance setbacks. By continuously monitoring class-wide trends, targeted bonus activities were introduced to support student improvement. This strategy reinforced the possibility of academic recovery through sustained effort and encouraged active cognitive and physical engagement during class sessions. Based on student performance at the point illustrated in Fig. 4(b), additional in-class bonus opportunities were implemented to help students partially recover from observed declines in performance.

As noted earlier, the course underwent a major redesign to incorporate iterative weekly mini-projects that collectively contributed to a final project worth 5% of the course grade. These weekly projects were developed collaboratively with instructor guidance and required students to implement a graphical user interface (GUI) for a product refined throughout the semester. Consequently, consistent completion of weekly projects was critical. Analysis of class performance and iota metrics shown in Figure 4(a) and Figure 4(b) revealed that a significant proportion of students were not completing these projects, indicating a risk of further performance deterioration and potential failure to successfully demonstrate the final project.

By identifying this issue early using data generated by iota, instructional adjustments such as bonus opportunities and project restructuring were implemented as part of routine course management to support student learning. The present study retrospectively analyzes anonymized course data generated through these normal instructional practices. The instructional team restructured the final project component by dividing the original 5% allocation into two parts: Project 1 (1.5%) and Project 2 (3.5%). Project 1 required all students to complete the weekly mini-projects up to a defined milestone that enabled seamless continuation toward the final project. These weekly mini-projects were conducted during class with direct instructor support, and live demonstrations were recorded. This approach allowed students to revisit recorded sessions and successfully complete Project 1, thereby mitigating the risk of failure in the final project component.

Following the implementation of this strategy and the bonus opportunities, student performance improved, as shown in Figure 4(c). At this stage, grading data included eight laboratory assessments, eight homework assignments (with the lowest score dropped in accordance with course policy), Project 1, laboratory participation (3%), class participation and bonus activities (2%). Performance improved further after the evaluation of Project 2 and the allocation of additional bonus points in recognition of exceptional student effort, as illustrated in Figure 4(d).

Finally, Figure 4(e) presents the class grade distribution after the completion of the final Exam 3, including students who withdrew prior to the course drop deadline. Notably, 26 students ultimately received failing grades, 7 of whom had minimal participation from the beginning of the semester, completing only a few assessments before disengaging from the course.

Of the remaining 19 students, 11 exercised their option to withdraw from the course prior to the institutional drop deadline. Having been informed of their current academic standing through iota's predictive analytics, these students were able to make autonomous, well-informed decisions about course continuation with their academic advisors. Withdrawing allowed them to avoid a failing grade on their transcript and plan to retake the course under more favorable conditions. This proactive intervention allows students to justify a "W" rather than an "F" to employers, reflecting sound decision-making skills in critical situations.

Among the remaining eight students, one received an incomplete (I) grade, while seven ultimately did not pass the course. Two of these students were unable to complete a withdrawal prior to the institutional drop deadline, despite having received notifications regarding their projected academic outcomes. Their cases highlight the importance of early and sustained engagement with performance feedback, as well as the potential value of flexible institutional policies that account for students facing compounding challenges.

3.3. Comparison of iota predictive analytics and ultimate final grades

Due to variations in assessment difficulty, iota does not extrapolate performance from one assessment to another. For example, a student scoring 100% on the first lab does not imply a perfect score across the course. iota generates predictions by analyzing data within each assessment category; only assessments that have been completed, such as Lab 1, Homework 1, or Exam 1, are used to forecast the final grade. Categories without data are excluded, and students are notified that predictions may be inaccurate until sufficient data is available. For instance, in the course presented here, Exam 1 was conducted at the end of the first month, so early predictions were based solely on lab and homework scores, excluding exams until the first one was conducted.

Therefore, for accurate predictions, it is important to conduct at least one assessment from each category as early as possible. Early assessment allows students to view their predicted outcomes and plan the remainder of the semester accordingly. In addition, frequent assessments are pedagogically effective [11], [12], as they promote continuous engagement with course material and help students stay connected with the learning process.

3.4. iota grade prediction analysis (without bonus)

Realistic grade projections are computed based on students' cumulative average performance using only the assessment data available at a given point in time. Figure 5 illustrates the relationship between realistic projected grades and actual final grades (excluding bonus points) at four successive evaluation stages: (a) after Exam 1, (b) after Exam 2, (c) after Exam 2 but before Project 2, and (d) after Exam 2 and Project 2. Of the 171 students registered on iota, data from four students were excluded because they joined the platform after the mid-semester assessment, resulting in no available performance data prior to Exam 2.

After Exam 1 (Figure 5(a)), the projected grades already exhibit a clear positive correlation with the final outcomes. Despite being based on limited evidence, the projections successfully capture the relative performance distribution, distinguishing high-performing students from those at academic risk. Larger deviations are primarily observed among low-performing and high-variance students, which is expected at this early stage due to incomplete assessment coverage. These low-performing data points correspond to students who remained largely inactive from the beginning of the semester, as highlighted in Figure 4(e). At this stage, assessment data for class participation

(10%), lab participation (5%), and the project (5%) were unavailable; moreover, progress in other assessments cannot be reliably extrapolated to these components. Consequently, realistic projections in Figure 5(a) were computed out of 80%.

Following the inclusion of Exam 2 (Figure 5(b)), the alignment between predicted and actual grade distributions improves substantially. The predicted medians more closely track actual performance, and the dispersion within grade bands is reduced, indicating increased model stability and decreased uncertainty. This improvement suggests that incorporating multiple high-stakes assessments significantly enhances the reliability of performance forecasting. Projections in Figure 5(b) were computed out of 91.5%.

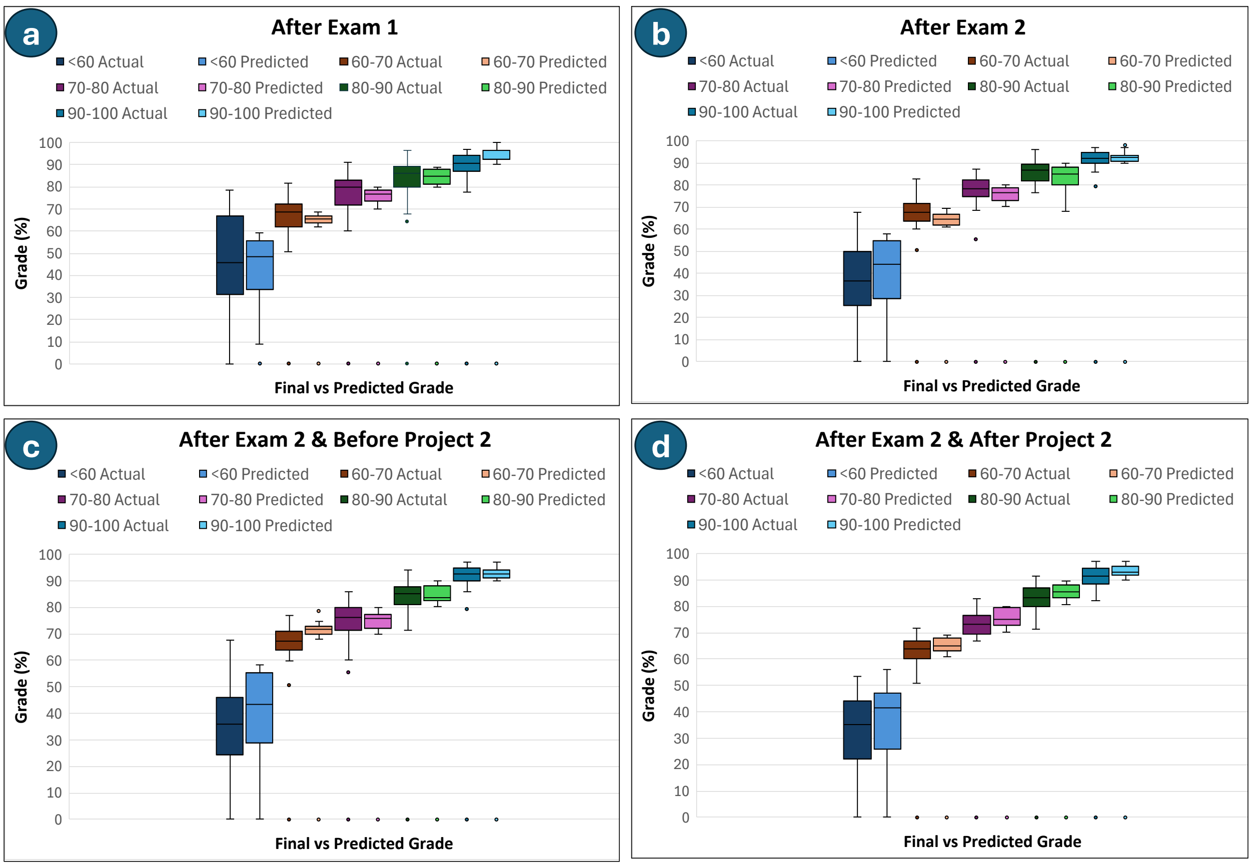


Figure 5. Comparison of realistic projected and actual student grade distributions across successive assessments.

Figure 5(c), evaluated after Exam 2 but before Project 2, shows sustained consistency between projected and actual grades across all performance bands. While minor discrepancies persist for students whose outcomes are more strongly influenced by project-based components not yet assessed, the projections remain academically conservative and continue to accurately stratify student performance. Projections in Figure 5(c) were computed out of 94.5%.

The strongest agreement is observed after incorporating both Exam 2 and Project 2 (Figure 5(d)), where assessment data from all grading categories are available and projections are therefore computed out of 100%. At this stage, predicted and actual grade distributions exhibit nearoverlapping medians and minimal variance across all grade bands, indicating near-convergent accuracy.

Overall, these results demonstrate that the proposed realistic grade prediction method exhibits progressive convergence toward actual outcomes as additional assessment data become available. Prediction uncertainty is highest at early stages and decreases monotonically over time, supporting the model's effectiveness for early risk identification, performance stratification, and final-grade estimation.

Similar pattern was observed in optimistic predictions versus actual grade obtained. *iota* allows instructors to set a prediction threshold that affects optimistic grade predictions. For example, we set the threshold to 95% for the presented course which assumes students might score at least 95% on future assessments. This gives students a small challenge and encourages them to try to do even better than the predicted grade. Most students usually get full marks on labs and homework but setting the threshold below 100% ensure that optimistic predictions remain attainable, especially for exams where stress is higher. Using a threshold below 100% helps students aim higher without giving them false expectations, motivating them to work harder to reach their goals.

3.5. Absolute Prediction Error and Correlation between Predicted and Actual Final Grades

Figure 6 illustrates the evolution of median absolute prediction error for realistic and optimistic grade predictions for all 167 students across multiple checkpoints during the semester. Overall, prediction accuracy improves as the semester progresses, reflecting the increasing availability of performance feedback.

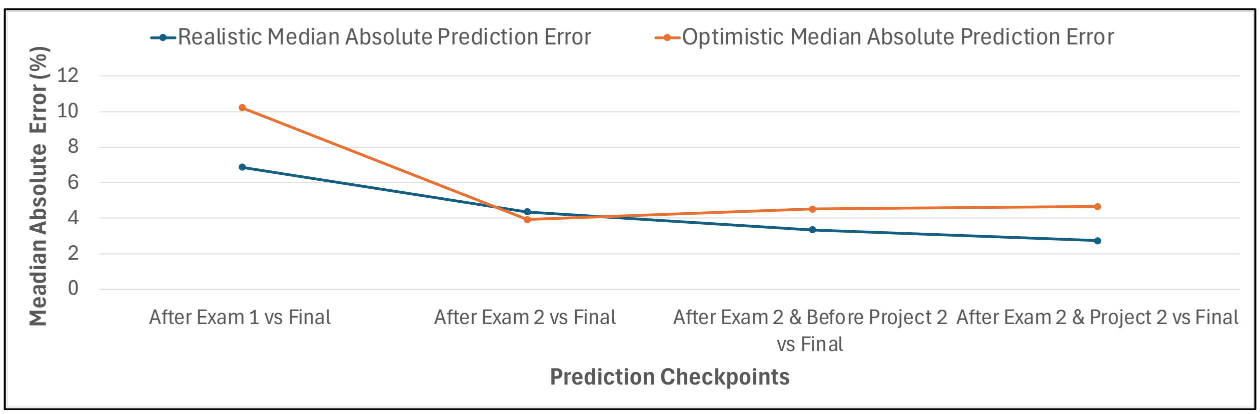


Figure 6. Median absolute prediction error for realistic and optimistic predictions across semester checkpoints.

Early in the term, after Exam 1, optimistic predictions exhibit substantially higher error than realistic predictions, indicating pronounced overconfidence when limited information is available. Following Exam 2, errors for both prediction types decrease markedly and converge, suggesting that additional assessment feedback improves calibration.

In the later part of the semester, realistic predictions continue to become more accurate as more assessment data is incorporated, including project performance, resulting in the lowest prediction error. In contrast, optimistic predictions stop improving and show a higher error level. This happens partly because the optimistic predictions made at the third and fourth checkpoints are compared against students' final grades, and for many high-performing students the final grade ends up higher than what they predicted at those checkpoints. In other words, these students were underpredicted (their optimistic predictions were below their eventual final outcomes). Specifically, predictions made at the third checkpoint for 34 students and at the fourth checkpoint for 24 students were lower than their eventual final grades, indicating underprediction. This effect becomes stronger after bonus points are added, increasing the number of students whose final grades exceed their predictions. When this happens, the gap between predicted and actual grades increases, which raises the absolute prediction error for optimistic predictions and reflects the presence of a substantial number of high-performing students in the class.

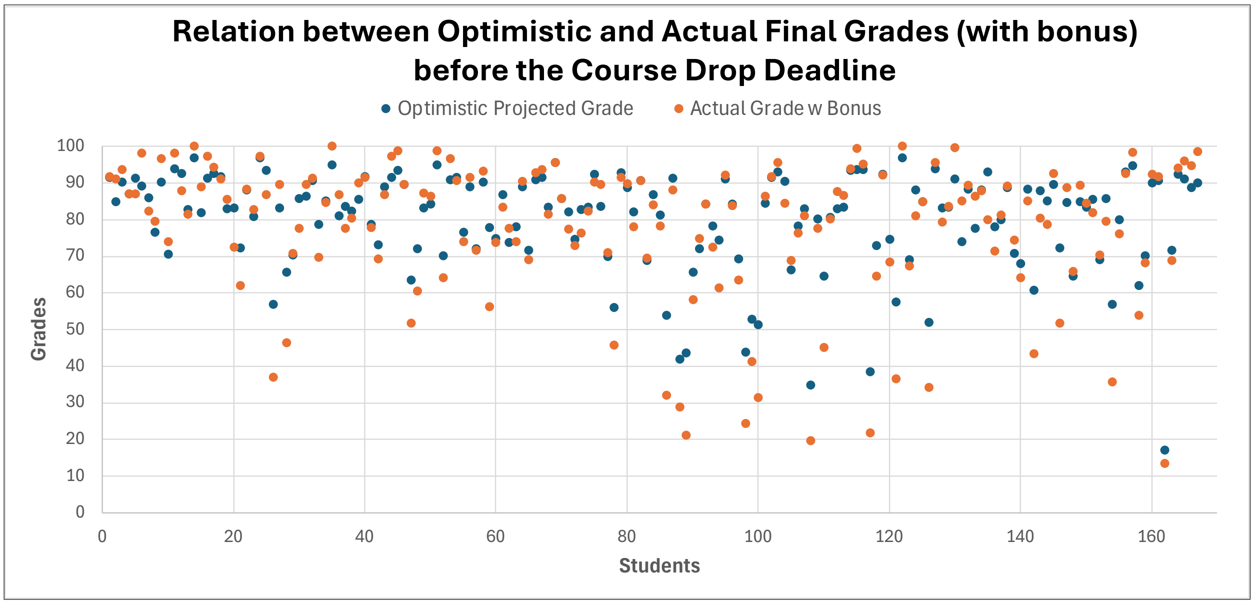


Figure 7. Scatter plot of optimistic projected grades versus actual final grades with bonus, illustrating high correlation despite notable over- and underprediction.

Figure 7 illustrates the relationship between students' optimistic projected grades and their actual final grades with bonus, based on predictions collected at a single point in time approximately one week before the course drop deadline, with the goal of better advising students at risk of failure. The scatter plot shows a clear positive association, with higher optimistic projections generally corresponding to higher final outcomes, a relationship confirmed by a strong Pearson correlation ($r \approx 0.91$). This indicates that students' optimistic predictions track relative performance well across the class. The dispersion observed in the plot is driven primarily by a subset of lower-performing students whose optimistic projections substantially exceed their final grades. Many of these cases correspond to students who subsequently dropped the course and did not appear for the final exam, resulting in markedly lower final outcomes than their earlier predictions. Excluding these students would lead to a closer alignment between optimistic predictions and final grades, particularly among continuing students. At the upper end of the distribution, several students achieved final grades exceeding their optimistic projections, especially after bonus points were applied, contributing to absolute prediction error while preserving the strong overall correlation.

3.6. Students' Feedback on iota

Student perceptions of iota were collected through an open-ended end-of-semester survey administered across multiple courses. Participation in the survey was voluntary and anonymous, and no identifying information was collected. Each non-empty response line was treated as an individual student response. Responses were coded into ordinal categories of perceived helpfulness (very/extremely helpful, helpful, somewhat/slightly helpful, not helpful, and did not use) using keyword-based sentiment grouping. This qualitative-to-quantitative coding approach enabled systematic aggregation and visualization of student feedback while preserving the overall distribution of sentiment.

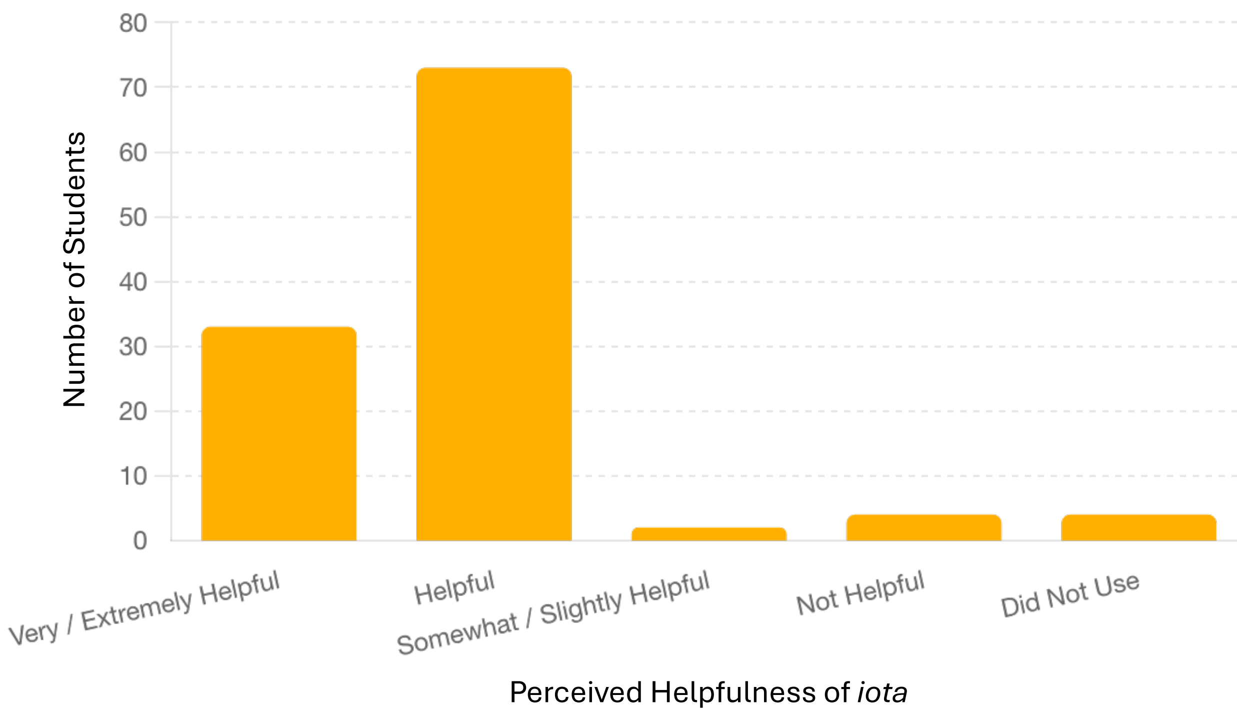


Figure 8. Distribution of student perceptions of iota's helpfulness, based on coded responses to an open-ended anonymous end-of-semester survey (n = 116).

Figure 8 summarizes student perceptions of iota's helpfulness across multiple courses based on 116 survey responses. The results show that a strong majority of students (over 90%) perceived iota as helpful or very helpful for monitoring their academic progress, with nearly two-thirds rating it as helpful and over one-quarter rating it as very or extremely helpful. Only a small fraction of respondents reported neutral, negative, or no-use experiences. These findings indicate broad student acceptance of iota and suggest that its grade monitoring and prediction features provide meaningful support for student awareness and decision-making.

4. Conclusions

This paper presented iota, a flexible and course-agnostic grade compilation, monitoring, and prediction platform designed to support both instructors and students throughout the academic term. By automating the aggregation of complex grading data and providing continuously updated realistic and optimistic performance projections, iota reduces instructor workload while increasing transparency and student awareness of academic standing. Its ability to process large-scale, fine-grained assessment data, such as that generated by automated platforms like zyBooks, makes it particularly well suited for modern, data-intensive courses.

Through deployment in a redesigned introductory programming course, we demonstrated how iota enables early identification of at-risk students, facilitates timely academic advising, and supports data-driven instructional adaptations. The platform's longitudinal grade distributions and predictive analytics allowed instructors to proactively adjust grading policies, introduce targeted bonus opportunities, and restructure project components in response to observed student performance trends. These instructional adjustments resulted in improved class performance and a reduction in the number of students failing the course.

Our analysis of prediction accuracy showed that both realistic and optimistic grade projections exhibit strong alignment with actual final outcomes, with prediction accuracy improving as additional assessments are completed. Median absolute prediction error decreased steadily across the semester, and optimistic projections showed a strong correlation with final grades ($r \approx 0.91$), indicating that students' expectations reliably tracked relative performance. Importantly, observed discrepancies in optimistic predictions were largely attributable to structural factors, such as course withdrawals and bonus-point adjustments, rather than fundamental flaws in the prediction model. When accounting for these factors, optimistic predictions align closely with final outcomes for continuing students.

Overall, our experience suggests how thoughtfully designed learning analytics tools, like iota, can support equitable advising, informed decision-making, and adaptive instruction in large courses. By combining accurate grade forecasting with intuitive visualizations and personalized reporting, tools like iota empowers students to make responsible academic choices and enables instructors to respond effectively to evolving classroom dynamics. Future work will explore broader deployment across disciplines, integration with institutional learning management systems, and the incorporation of additional behavioral and engagement signals to further enhance predictive robustness and student support.

Ethics Statement

This study was conducted in an established educational setting and involved the analysis of routine course data generated during normal instructional activities. All student performance data were de-identified prior to analysis, and no personally identifiable information was used in the research. Student feedback regarding the iota platform was collected through an anonymous, voluntary end-of-semester survey, and participation had no effect on course grades or academic standing. Data analysis was conducted only after final course grades had been submitted, ensuring that the analysis did not influence student evaluation or grading decisions. The authors declare that no individual students can be identified from the data or findings reported in this manuscript.

Author Contributions

Hasan Baig conceived and led the development of the initial iota prototype, directed the architectural design of the cloud-based platform, and holds the intellectual property for the system. He administered the course whose analytics and pedagogical outcomes are examined in this manuscript, oversaw data collection throughout the semester, and was the primary author responsible for writing the original draft of the manuscript.

Matthew R. Fletcher led the rigorous quantitative analysis of student performance data collected across the semester, including the evaluation of prediction accuracy, grade distribution trends, and correlation metrics. He contributed to the interpretation of analytical results and assisted in the preparation and revision of the data-driven sections of the manuscript.

Kriti Bhargava provided pedagogical validation and functional testing of iota by independently deploying the platform across three distinct courses at varying academic levels. She contributed substantively to the analytical framework of the manuscript, guided the comparative analysis of predictive versus actual grade distributions, and provided a thorough critical review of the complete manuscript.

Ibraheem Tasneem led the end-to-end technical development of the iota platform, including the implementation of its core grading, prediction, and communication features. He was responsible for the software engineering infrastructure underpinning the cloud-based system and contributed to iterative testing and refinement of the platform throughout its deployment.

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