Deciphering the Influence of Mid-term Examinations on Student Learning Outcomes: A Comprehensive Investigation Employing Statistical and Machine Learning Approaches

Liyuan Liu[1,]* and Meng Han[2]

[1] Department of Decision and System Sciences, Saint Joseph's University, Philadelphia, USA
[2] Binjiang Institute, Zhejiang University, Zhejiang, China
Email: lliu@sju.edu (L.L.); mhan@zju.edu.cn (M.H.)
*Corresponding author

***Abstract*—It is widely recognized that mid-term examinations serve as a fundamental assessment method for evaluating students' learning progress at the midpoint of a semester. A plethora of previous studies have underscored the significance of mid-term exams as a determinant of final grades, exhibiting a positive correlation with final exam outcomes. Nevertheless, these investigations frequently analyze the entire student population without accounting for disparities in students' mental states and learning objectives, particularly in the aftermath of receiving their mid-term exam results. In the present study, we scrutinize the mid-term and final grades of 171 students participating in a statistics course. Diverging from prior research, which typically employs the entire student data as a singular group, we partition students into two distinct categories: those who attain higher mid-term exam scores and those who secure lower mid-term exam scores. Our analysis reveals that students achieving higher mid-term exam scores are more likely to obtain lower final exam scores, while students with lower mid-term scores tend to attain superior final exam results. This phenomenon is attributed to the influence of learning from failure, which motivates students who initially underperform to adopt new strategies and strengthen their learning objectives. Furthermore, we utilize a non-linear Support Vector Machine (SVM) model to forecast students' final performance, recognizing that learning is a non-linear process replete with uncertainties. The model's interpretation discloses that the mid-term exam and assignments administered during the mid-term exam period constitute the most influential factors impacting students' final performance. Consequently, the meticulous monitoring of students' mid-term grades and the implementation of strategic incentives to bolster their learning outcomes are paramount for ensuring their success in academic courses.**

***Keywords*—adjusting teaching strategies, student performance prediction, mid-term exam, machine learning in education**

Manuscript received April 17, 2023; revised June 25, 2023; accepted July 10, 2023; published January 10, 2024.

I. INTRODUCTION

In recent times, a significant proportion of college students continue to experience anxiety pertaining to mathematics and statistics courses, primarily due to stress-induced feelings [1]. Anxiety can considerably impact students' learning outcomes, leading to lower academic achievement and increased absenteeism rates [2]. According to previous studies, mathematics courses consistently exhibit higher withdrawal and dropout rates compared to other disciplines. High failure and withdrawal rates in introductory post-secondary mathematics courses pose challenges at local, national, and international levels. Presently, Failure and Withdrawal (FDVW) rates in undergraduate mathematics courses across North America and internationally are alarmingly high, ranging from 30% to as much as 60% [3]. Consequently, enhancing students' learning outcomes and preventing withdrawals in STEM courses in higher education is of utmost importance. As widely acknowledged, mid-term exams serve as a standard evaluation method to gauge students' learning progress midway through the semester. Students' mid-term exam grades play a vital role in assessing their need to withdraw or invest greater effort into the course. In past studies, numerous researchers have identified mid-term exams as a critical factor influencing final grades, with a positive relationship to final exam scores [4–7]. However, both studies treated all students as an entire sample and ignored the fact that students' mental states and learning engagement vary with different mid-term exam grades. Learning is a continuous process, and students' mental status after the mid-term exam can affect their final performance. Students with higher mid-term exam grades may exert less effort in the course after the mid-term exam due to trade-offs with other concurrent courses. Conversely, students with lower mid-term exam grades may invest more effort in the course after the mid-term exam. Therefore, unlike previous studies, we divide students into two groups: those with higher mid-term exam grades and those with lower mid-term exam grades.

doi: 10.18178/ijlt.10.1.32-39

Intriguingly, our study reveals that students in the higher mid-term exam grade group tend to obtain lower final exam grades, whereas students in the lower mid-term exam grade group tend to achieve better final exam results. Additionally, we found that predicting final exam grades involves a non-linear correlation; using non-linear machine learning models to predict students' final grades proved more accurate than linear models, which most previous studies employed. Consequently, we determined that adjusting teaching strategies and designing personalized teaching strategies for different students after mid-term exams are crucial for instructors to help students achieve academic success, particularly in light of students' psychological changes.

Interestingly, the psychological concept of the "underdog effect" may also play a role in shaping students' attitudes and behaviors following the receipt of their grades [8]. In the realm of education, the underdog effect can help explain why students who receive lower mid-term exam grades may exhibit a higher final grade. The term "underdog" refers to individuals or groups perceived as being at a disadvantage or having lower status, which can motivate them to work harder and demonstrate a greater determination to succeed [9]. In an academic setting, students who receive lower mid-term grades might perceive themselves as underdogs, motivating them to put forth greater effort in their coursework to improve their performance. This increased effort can lead to a higher final grade, as it reflects their determination to overcome their initial disadvantage. Additionally, the underdog effect can trigger social support from teachers and peers, who might empathize with these students and offer guidance or encouragement, further boosting their motivation [10]. From a psychological perspective, students experiencing the underdog effect might also adopt a growth mindset [11]. They may view their low mid-term grades as an opportunity for improvement, rather than a fixed representation of their abilities. This growth mindset can foster resilience and persistence in the face of challenges [12], ultimately contributing to improved academic performance. Furthermore, self-regulation strategies, such as goal-setting, time management, and seeking feedback, may be employed by these students to enhance their learning process and attain higher final grades [13].

In order to prove our assumptions, we employed two student groups to determine whether mid-term exam grades impact students' learning outcomes in an introductory statistics course. The primary contributions of this study are as follows:

- Unlike previous research that used a single group of students, we created two models to investigate the distinct trends in correlations between mid-term and final exam grades for different student groups. Our findings reveal the underdog effect and the importance of learning from failure, showing that students with lower mid-term exam grades tend to achieve better final grades.
- We emphasized the importance of monitoring students' mid-term grades and implementing personalized incentive strategies to enhance learning outcomes in STEM courses, considering the psychological changes students experience after mid-term exams and the potential for growth through learning from failure.
- Recognizing the non-linear nature of factors influencing final course grades, we employed non-linear machine learning models, such as SVM, instead of traditional linear models used in previous research, offering a more accurate and reproducible approach for future instructors.
- To address the interpretability challenge in machine learning, we applied the Shapley Value, a game theory algorithm, to identify and rank factors influencing students' learning outcomes using SVM models.

II. Related Works

Numerous researchers have considered the mid-term exam as a critical predictor of students' final grades. Table I presents a summary of related literature in this area. Predominantly, these studies have employed conventional statistical methods for predictions, finding a positive correlation between mid-term and final exams. However, learning is an ongoing process, and students' mental activities and study goals may shift following satisfaction or disappointment with their mid-term grades. In contrast to previous studies using one model, our research conducts two segment models and uncovers a different relationship for students in these two groups.

TABLE I. Related Studies between Mid-term and Final Grades

Related Works	Model	Correlation between Mid-term and Final Exams	Class Type
Dambolena 2000 [4]	Linear Regression	Positive	Mathematics
Gamulina *et al.* 2013 [5]	Principal Component Regression Partial Least Square Regression	Positive	Physics and Hybrid
Glick *et al.* 2019 [6]	Correlation Coefficient	Positive	English Language and Online
Jensen *et al.* 2014 [7]	Statistical Analysis	Positive	Biology and In-person
Porter *et al.* 2014 [15]	Correlation Coefficient	Positive	Computer Science
You 2016 [26]	Hierarchical Regression	Positive	Online Course
Hasan *et al.* 2019 [27]	Correlation Coefficient	Positive	Not Available

In the context of academic performance, students who receive higher grades may become overconfident and complacent, resulting in reduced attention and effort devoted to the course [14]. Conversely, students who obtain lower grades may embrace the role of the underdog, experiencing a heightened sense of determination and resilience, which leads to increased attention and effort in their studies [15]. This underdog mentality can serve as a powerful motivator for low-performing students, driving them to overcome challenges and strive for academic success [16].

The underdog narrative has been a popular theme in business, with numerous success stories highlighting the triumph of small companies or entrepreneurs over larger, more established competitors. Gunn and Stevens [17] examined the effect of social support on undergraduate students' perceptions of underdogs in business. They found that students who perceived social support were more likely to favor underdogs in business contexts. The underdog phenomenon has been widely explored in various fields, including education, management, and sports. McGinnis [18] provided an inspiring example of Indian athletes who succeeded against established competitors. In management literature, the underdog effect has been linked to fairness, motivation, and decision-making, with studies showing preferences for options favoring underdogs [19].

In education, the underdog phenomenon has been examined concerning student motivation, achievement, and persistence. Research has shown that students who believe in their ability to develop intelligence, similar to underdogs, are more likely to demonstrate academic improvement [11]. Underdog students who view intelligence as malleable tend to adopt adaptive coping strategies when facing academic challenges, promoting resilience and academic success [12]. Furthermore, self-regulated learning is crucial for underdog students to enhance their motivation, engagement, and performance [13].

Moreover, the advancement of Artificial Intelligence (AI) has led to an increasing number of applications utilizing machine learning algorithms (e.g., linear regression, logistic regression, deep neural networks, recurrent neural networks) for making predictions, superseding traditional statistical methods. It has been observed that non-linear machine learning or deep learning algorithms possess significant advantages, as they can effectively address uncertainties and non-linear relationships between dependent and independent variables [20]. In higher education, researchers have begun incorporating AI algorithms for education-based analysis. Fig. 1 presents recent machine learning-based educational research [21–25]. Utilizing Support Vector Machines (SVM) for predicting students' final grades is indeed an application of AI in education. In this study, we diverge from prior research that primarily employed linear models for predicting students' outcomes. Instead, we incorporate non-linear machine learning algorithms, such as SVM, to predict students' final learning outcomes more accurately and effectively.

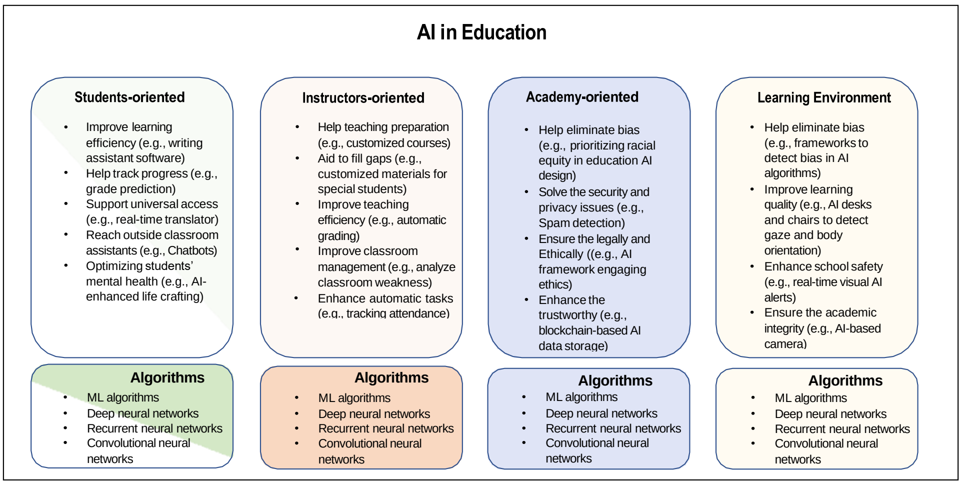

Fig. 1. AI in education.

III. Methods

A. Participants

The dataset comprises 171 students enrolled in a Business Statistics course at an AACSB-accredited business school in Pennsylvania, USA. The students consist of 23 freshmen, 142 sophomores, and 6 juniors, distributed across six sections of the course. A single instructor teaches all sections, ensuring consistency in teaching materials, exam questions, and grading rubrics. The exams are administered on paper and feature 10 short answer questions. To support student preparation, two review sessions are conducted for both exams. The average mid-term exam grades for freshmen, sophomores, and juniors are 81.9, 90.1, and 91.1, respectively. The average final exam grades for these groups are 85.7, 92.0, and 92.3, respectively. The descriptive statistics for the mid-term and final exams across the higher and lower mid-term exam grade groups as Group L (students with lower mid-term exam grades) and Group H (students with higher mid-term exam grades) are presented in Table II, Group L represents the lower 50th percentile, while Group H represents the upper 50th percentile.

Table III illustrates the difference in grades between the mid-term and final exams (final exam grades minus mid-term exam grades). Group H exhibits a negative change, indicating that the mid-term exam grades surpass the final exam grades within this group. This observation serves as evidence to support our hypothesis that students with higher mid-term exam grades are more likely to achieve lower final exam grades. Conversely, the mean change for Group L is positive, suggesting that students with lower mid-term exam grades are more likely to obtain higher final grades.

TABLE II. DESCRIPTIVE STATISTICS FOR MID-TERM AND FINAL GRADES

Group	Exam	Count	Mean	Standard Deviation
Group L	Mid-term	86	71.01	17.29
	Final	86	84.31	18.15
Group H	Mid-term	85	96.22	3.29
	Final	85	93.15	12.43

TABLE III. GRADES CHANGES BETWEEN MID-TERM AND FINAL EXAMS

Changes between Mid-term and Final Exams (Final-Mid-term)	Count	Mean	Standard Deviation
Group L	86	13.29	24.73
Group H	85	−3.07	11.27

B. Statistical Analysis and Hypothesis Tests

In this study, we first examined two scatter plots to visualize the relationship between mid-term and final exam grades for both Group H and Group L, as Figs. 2 and 3 show. Both scatter plots revealed a positive linear correlation, indicating a direct relationship between mid-term and final exam performance within each group. The correlation coefficients for Group H and Group L were found to be 0.28 and −0.09, respectively.

The results of this analysis have implications for understanding the role of underdogs and learning from failure in academic contexts. The negative correlation (−0.09) observed in Group L reveals an intriguing pattern: students with initially lower mid-term exam grades tend to exhibit higher final exam performance. This unexpected trend suggests that students in Group L, despite their lower mid-term grades, demonstrate a remarkable ability to improve and excel in their final exams. This phenomenon challenges conventional expectations and can be attributed to various factors. One possible explanation is that students in Group L, faced with lower mid-term grades, experience a heightened motivation to learn from their earlier setbacks. This increased motivation may drive them to engage in self-reflection, identify areas of improvement, and adopt more effective learning strategies.

The concept of learning from failure becomes particularly relevant here, as students who encounter lower performance in mid-term exams may be more inclined to view it as an opportunity for growth. By leveraging their setbacks as learning experiences, these students develop resilience and a growth mindset, allowing them to enhance their academic performance in the final exams.

The findings of this study underscore the importance of fostering resilience and providing support for students, especially those who initially struggle. Educational institutions should strive to create an environment that encourages self-reflection, promotes effective learning strategies, and instills a growth mindset. By doing so, we can empower students in Group L to overcome their challenges, leverage their failures as learning opportunities, and achieve notable improvements in their final exam performance.

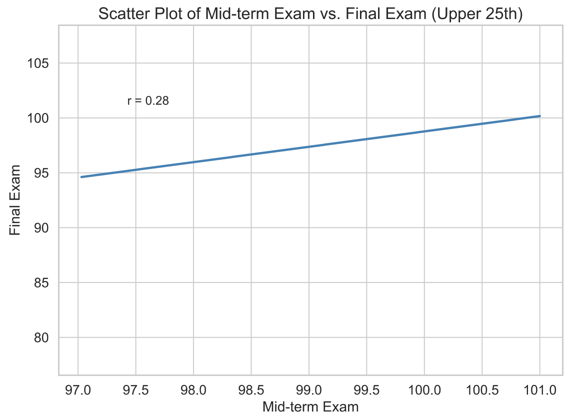

Fig. 2. Scatter plot of mid-term exam vs. final exam (upper 25th).

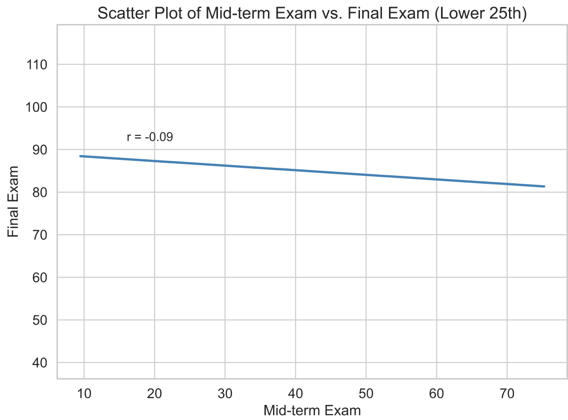

Fig. 3. Scatter plot of mid-term exam vs. final exam (lower 25th).

In addition, we employ hypothesis testing as a robust statistical approach to investigate the potential differences in final exam performance between two distinct groups of students. We can represent the average mid-term exam grade for Group L as μ_{Lm} and their average final exam grade as μ_{Lf}. Similarly, for Group H, we can represent the average mid-term exam grade as μ_{Hm} and their average final exam grade as μ_{Hf}.

In this study, we stratified students into two distinct groups based on their mid-term exam performance: Group L and Group H. We observed that the students in Group L exhibited lower mid-term exam grades but higher final exam grades compared to their counterparts in the Group H. To assess the significance of the mid-term exam grade differences between these two groups, we conducted two separate hypothesis tests. We designed one hypothesis tests using the following notation:

H_0^1: *The average mid-term exam grade for Group H is not significantly different from or is less than that of Group L, i.e.,* $\mu_{Hm} - \mu_{Lm} \leq 0$.

H_1^1: *The average mid-term exam grade for Group H is significantly greater than that of Group L, i.e.,* $\mu_{Hm} - \mu_{Lm} > 0$.

H_0^2: The average final exam grade for Group H is not significantly different from or is greater than that of Group L, i.e., $\mu_{Hm} - \mu_{Lm} \geq 0$.
H_1^2: The average final exam grade for Group H is significantly lower than that of Group L, i.e., $\mu_{Hm} - \mu_{Lm} < 0$.

TABLE IV. HYPOTHESIS TESTS FOR MID-TERM EXAM GRADES BETWEEN GROUP H AND GROUP L

Hypothesis Test Set	Difference (Group H and Group L)	Degrees of Freedom	T	P-value
$H_0{}^1$ and $H_1{}^1$	25.20	169	13.2	< 0.001
$H_0{}^2$ and $H_1{}^2$	8.84	169	3.71	< 0.001

The p-value for both the mid-term and final exams is less than 0.001, indicating that the performance of Group H is significantly superior to that of Group L in both evaluations. However, the difference between the two groups is more pronounced in the mid-term exam, with Group H scoring 25.2 points higher on average, compared to an 8.84 points difference on the final exam. This discrepancy suggests that Group H's performance declined from the mid-term to the final exam. It validates our initial assumption that students who excel in the mid-term exam are likely to experience a decrease in performance in the final exam.

In addition to comparing the grades between Group H and Group L, we also sought to investigate the changes in the grade distribution within each group. To this end, we conducted four additional hypothesis tests to demonstrate the tendencies that students with higher mid-term exam scores within their respective groups are more likely to have lower final exam scores, while students with lower mid-term exam scores are more likely to have higher final exam scores. Since our analysis focuses on comparisons within each group, the influence of external variables is minimized. By conducting t-tests within the groups, we can isolate the effects of mid-term exam performance on final exam scores, thereby providing a more nuanced understanding of the relationship between mid-term and final exam performance for students in both Group H and Group L. To assess the significance of the differences between mid-term and final exam grades within the four sections, we conducted four hypothesis tests in this study. The tests are outlined as follows, we use μ' represents the mean of grades change (final exam grades-mid-term exam grades):
H_0^3: For students in Group H, $\mu_H' \geq 0$; *H_1^3: For students in Group H,* $\mu_H' < 0$.
H_0^4: For students in Group L, $\mu_L' \leq 0$; *H_1^4: For students in Group L,* $\mu_L' > 0$.

TABLE V. HYPOTHESIS TESTS FOR DIFFERENCE BETWEEN MID-TERM AND FINAL EXAMS WITHIN GROUP

Hypothesis Test Set	Degrees of Freedom	T	P-value
$H_0{}^3$ and $H_1{}^3$	84	−7.69	0.007
$H_0{}^4$ and $H_1{}^4$	85	4.98	< 0.001

Table IV presents the results of the t-statistics and p-values. The findings indicate that the mid-term exam grades are statistically significantly lower than the final exam grades for Group H. Conversely, the mid-term exam grades are significantly higher than the final exam grades for Group L. All hypothesis tests yielded p-values less than 0.05, highlighting the significance of the observed differences. Table V presents the results of the t-statistics and p-values for the difference between mid-term and final exams within groups. All four hypothesis tests yield smaller p-values, leading to the acceptance of our alternative hypotheses. These results reveal a noteworthy pattern: students with lower mid-term exam grades are more likely to achieve better final exam grades. This finding contradicts previous research, which suggests a positive correlation between mid-term and final exam performance. Mid-term exams serve as a self-evaluation process that can influence students' learning attitudes. As such, it is vital for educators to adjust their teaching strategies and motivate students to maintain their efforts after the mid-term exam, particularly for those who initially perform well. Learning is a dynamic process, with students' motivation and perspectives evolving based on their achievements. Our findings are further supported by previous research, which indicates that learning is enhanced when teachers adapt their instruction in response to students' changing conceptions [28].

C. Employing Non-linear SVM to Predict Students' Final Performance

As discussed in Section II, numerous researchers have utilized linear models to predict students' final grades. However, students' final performance is not strictly linear, and the learning process encompasses multiple uncertainties. In contrast to prior research employing linear regression for predicting students' final grades, we implemented a non-linear machine learning model, specifically, a non-linear Support Vector Machine (SVM), to predict students' final performance. SVM is a machine learning algorithm designed to efficiently learn good linear separating hyperplanes within high-dimensional datasets [29]. It can be applied to both regression and classification tasks. Kernel functions can be incorporated into linear SVM models to manage non-linear datasets, transforming them into specific forms. If we have a high-dimensional dataset denoted as x that needs to be transformed into a feature space ϕ(x), the kernel function can be defined as:

$$K_{ij} = k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j) \tag{1}$$

Several kernel functions can transform non-linear data into a feature space that makes the data more likely to be linearly separable, such as polynomial, Radial Basis Function (RBF), and sigmoid. In this study, we employed the RBF kernel function to predict students' final performance. The formula for Radial Basis Function Kernel is below:

$$k(x_i, x_j) = exp(-1/2\sigma^2 \, \|x_j - x_i\|^2) \tag{2}$$

The RBF kernel is widely considered the most generalized and popular kernel function due to its similarity to the Gaussian distribution [30].

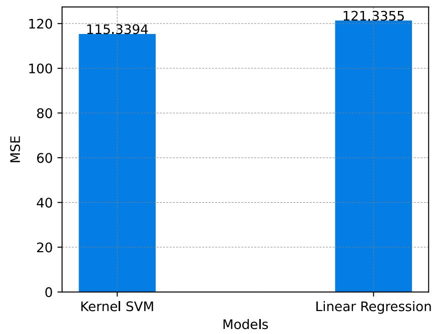

Fig. 4. MSE using the original dataset.

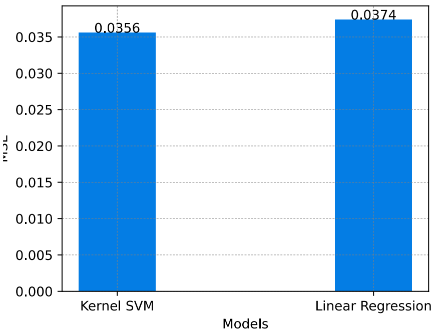

Fig. 5. MSE after normalization.

In comparison to linear regression, non-linear SVM can accommodate nonlinearity and perform better if a non-linear relationship exists between independent and dependent variables. Learning is a multifaceted process, and numerous factors affect student learning outcomes beyond grades, such as communication, learning facilities, proper guidance, and family stress. Thus, using non-linear SVM to predict students' final learning outcomes can better assist instructors in adjusting their teaching strategies and enhancing students' learning quality. We employed both non-linear SVM and linear regression to predict students' final grades using assignment grades, mid-term exam grades, and class participation grades. Figs. 4 and 5 illustrate the models' performance using Mean Squared Error (MSE). The results demonstrate that non-linear SVM achieves superior model performance compared to linear regression. Moreover, we employed the Shapley Value to illustrate the importance of features. Many previous studies have avoided using black box models due to their inherent complexity and difficulty in interpretation. However, in this study, we utilized the Shapley Value, a game theory algorithm, to elucidate the model. Fig. 6 presents the feature ranking, with the mid-term exam emerging as the most influential factor affecting students' final performance. Another noteworthy finding is that Assignments 4 and 5 rank as the second and third most important determinants of final grades. Assignment 5, the first assignment after the mid-term exam, and Assignment 4, the last assignment before the mid-term exam, reveal that students' learning persistence fluctuates throughout the middle of the semester. Consequently, instructors should adapt their teaching strategies and pay greater attention to students' engagement during the mid-semester period.

The method of utilizing SVM to predict students' performance in advance is not limited to just statistics classes; it can be applied across various courses. The versatility of SVM allows its application in different academic disciplines, offering valuable insights into students' potential achievements before they even occur. Compared to using a linear model, SVM provides several distinct benefits. Firstly, SVM is capable of handling complex, nonlinear relationships between predictors and outcomes, which often exist in educational datasets. This flexibility allows SVM to capture intricate patterns and correlations that may go unnoticed when using a linear model. Secondly, SVM employs a kernel function that can transform the original features into a higher-dimensional space. This transformation enables SVM to effectively separate data points, especially in cases where linear separation is not feasible. By utilizing this nonlinear mapping, SVM maximizes the accuracy and reliability of the performance prediction model, enhancing its predictive power. Furthermore, SVM employs a margin-based approach, aiming to find an optimal decision boundary that maximizes the distance between data points of different classes. This characteristic of SVM leads to improved generalization performance, meaning it can better handle new, unseen data. In educational contexts, this translates into the ability to predict students' performance accurately even for individuals not present in the initial training dataset. Therefore, the application of SVM for predicting students' performance is not limited to statistics classes but can be extended to any academic course. Its advantages over linear models, such as handling nonlinear relationships, employing higher-dimensional transformations, and achieving improved generalization, make SVM a powerful and versatile tool in educational data analysis. By leveraging SVM, educators and institutions can gain valuable insights into students' future performance, enabling targeted interventions and support to enhance their learning outcomes.

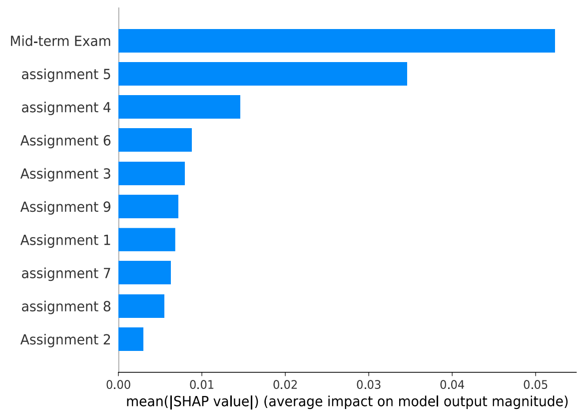

Fig. 6. Features ranking using Shapley values.

IV. Conclusion

In conclusion, this study investigated the relationship between students' mid-term exam performance and their final exam outcomes, taking into account various factors and employing both linear and non-linear models. Our findings suggest that students with lower mid-term exam grades are more likely to exhibit improvements in their final exam performance compared to those with higher mid-term exam grades, emphasizing the underdog phenomenon and the potential benefits of learning from failure. Moreover, we discovered that the underdog effect and learning from failure are particularly relevant during the mid-semester period, necessitating that instructors adjust their teaching strategies and pay greater attention to student engagement at this critical juncture.

Additionally, we employed a non-linear SVM model to predict students' final performance more accurately than linear regression, considering the complex nature of learning processes and various influencing factors. Furthermore, the Shapley Value was utilized to rank the importance of features, revealing that the mid-term exam is the most influential determinant of students' final performance.

This study contributes to the existing literature on student performance and pedagogical approaches by highlighting the importance of continuous monitoring of students' progress and adjusting teaching strategies accordingly, taking into account the underdog effect and the potential for learning from failure. The insights gleaned from this research can help educators and policymakers develop more effective interventions that cater to the diverse learning needs of students, ultimately enhancing their academic outcomes and overall educational experience. Future research could expand the scope of this study by incorporating additional variables, such as socio-economic background and psychological factors, as well as exploring the impact of different pedagogical approaches on student performance.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Liyuan Liu conducted the investigations and experiments, collected and analyzed the data, and was primarily responsible for writing the initial draft of the manuscript; Meng Han validated the results, critically reviewed the manuscript, and provided valuable feedback for improvement; all authors had approved the final version.

References

[1] M. Cumhur and M. Tezer, "Anxiety about mathematics among university students: A multi-dimensional study in the 21st century," *Cypriot Journal of Educational Sciences*, vol. 14, no. 2, pp. 222–231, 2019.

[2] M. E. A. Ruz, H. Y. Al-Akash, and S. Jarrah, "Persistent (anxiety and depression) affected academic achievement and absenteeism in nursing students," *The Open Nursing Journal*, vol. 12, p. 171, 2018.

[3] D. Barr and L. Wessel, "Rethinking course structure: Increased participation and persistence in introductory post-secondary mathematics courses," *Fields Mathematics Education Journal*, vol. 3, pp. 1–13, 2018.

[4] I. G. Dambolena, "A regression exercise: Predicting final course grades from midterm results," *Problems, Resources, and Issues in Mathematics Undergraduate Studies*, vol. 10, no. 4, pp. 351–358, 2000.

[5] J. Gamulin, O. Gamulin, and D. Kermek, "Data mining in hybrid learning: Possibility to predict the final exam result," in *Proc. 2013 36th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, IEEE, 2013, pp. 591–596.

[6] D. Glick, A. Cohen, E. Festinger, *et al.*, "Predicting success, preventing failure," in *Utilizing Learning Analytics to Support Study Success*, Springer, 2019, pp. 249–273.

[7] P. A. Jensen and J. N. Barron, "Midterm and first-exam grades predict final grades in biology courses," *Journal of College Science Teaching*, vol. 44, no. 2, pp. 82–89, 2014.

[8] J. A. Vandello and J. K. Bosson, "Hard won and easily lost: A review and synthesis of theory and research on precarious manhood," *Psychology of Men & Masculinity*, vol. 14, no. 2, pp. 101–113, 2007.

[9] S. Nurmohamed, "The underdog effect: When low expectations increase performance," *Academy of Management Journal*, vol. 63, no. 4, pp. 1106–1133, 2020.

[10] G. R. Gunn and C. Stevens, "The effect of social support on undergraduates' perceptions of the underdog," *North American Journal of Psychology*, vol. 15, no. 3, pp. 495–506, 2013.

[11] L. S. Blackwell, K. H. Trzesniewski, and C. S. Dweck, "Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention," *Child Development*, vol. 78, no. 1, pp. 246–263, 2007.

[12] D. S. Yeager and C. S. Dweck, "Implicit theories, attributions, and coping: A meaning system approach," *Journal of Personality and Social Psychology*, vol. 103, no. 3, pp. 460–476, 2012.

[13] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," *Theory into Practice*, vol. 41, no. 2, pp. 64–70, 2002.

[14] D. Dunning, K. Johnson, J. Ehrlinger, and J. Kruger, "Unskilled and unaware of it: How difficulties in recognizing one's own in-competence lead to inflated self-assessments," *Journal of Personality and Social Psychology*, vol. 77, no. 6, 1121, 1999.

[15] P. R. Pintrich, "A motivational science perspective on the role of student motivation in learning and teaching contexts," *Journal of Educational Psychology*, vol. 95, no. 4, 667, 2004.

[16] R. K. Merton, "The Matthew effect in science," *Science*, vol. 159, 3810, pp. 56–63, 1968.

[17] J. McGinnis, *Underdogs: How Two Indian Athletes Beat the Billion Dollar Shoe Industry*, Lulu, 2009.

[18] M. M. Pillutla and J. K. Murnighan, "Is it better to be poor but smart or rich but dumb? Unfairness, underdogs, and the attractiveness of options," *Journal of Experimental Social Psychology*, vol. 34, no. 2, pp. 134–150, 1998.

[19] L. Liu, M. Han, Y. Zhou, and Y. Wang, "LSTM recurrent neural networks for influenza trends prediction," in *Proc. International Symposium on Bioinformatics Research and Applications*, Springer, 2018, pp. 259–264.

[20] A. Halim, S. Sharina, and S. Zur, "Grammarly as a tool to enhance students' self-directed learning," *KnE Social Sciences*, pp. 5–13, 2022.

[21] N. Nazari, M. S. Shabbir, and R. Setiawan, "Application of artificial intelligence powered digital writing assistant in higher education: Randomized controlled trial," *Heliyon*, vol. 7, no. 5, e07014, 2021.

[22] G. Taasoobshirazi, M. Wagner, A. Brown, and C. Copeland, "An evaluation of college students' perceptions of statisticians," *Journal of Statistics and Data Science Education*, pp. 1–16, 2022.

[23] G. Terzopoulos and M. Satratzemi, "Voice assistants and artificial intelligence in education," in *Proc. the 9th Balkan Conference on Informatics*, 2019, pp. 1–6.

[24] M. C. Wijaya, "Automatic short answer grading system in Indonesian language using Bert machine learning," *Rev. d'Intelligence Artif.*, vol. 35, no. 6, pp. 503–509, 2021.

[25] J. W. You, "Identifying significant indicators using LMS data to predict course achievement in online learning," *The Internet and Higher Education*, vol. 29, pp. 23–30, 2016.

[26] H. R. Hasan, A. S. A. Rabby, M. T. Islam, and S. A. Hossain, "Machine learning algorithm for student's performance prediction," in *Proc. 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, IEEE, 2019, pp. 1–7.

[27] M. L. Crawford, "Teaching contextually," in *Research, Rationale, and Techniques for Improving Student Motivation and Achievement in Mathematics and Science*, Texas: Cord, 2001.

[28] M. Hofmann, "Support vector machines-kernels and the kernel trick," *Notes*, vol. 26, no. 3, pp. 1–16, 2006.

[29] C. Yang, R. Duraiswami, and L. Davis, "Efficient mean-shift tracking via a new similarity measure," in *Proc. 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, IEEE, 2005, vol. 1, pp. 176–183.

[30] I. Mushtaq and S. N. Khan, "Factors affecting students' academic performance," *Global Journal of Management and Business Research*, vol. 12, no. 9, pp. 17–22, 2012.