Academic Success and Retention Pathway for Mechanical Engineering Major

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In 2021, Dr. Ofori-Boadu was selected as one of six female faculty to be highlighted in the Center of Product Design and Advanced Manufacturing (CEPDAM) video during Women's History Month. She was also recognized as a 2021 College of Science and Technology STEMinist. Andrea also served as an NSF HBCU-UP Distinguished Panelist at NSF's 30th anniversary celebration of broadening participation. She received the 2020 Outstanding Educator award from the National Association of Home Builders and the 2020 Junior Faculty Teaching Excellence Award at North Carolina Agricultural and Technical State University. In 2019, Andrea received the Outstanding Young Investigator award for both North Carolina A & T State University and the College of Science and Technology. In 2018, she was selected as a 2018 National Science Foundation - NC A & T ADVANCE IT Faculty Scholar. She also received the 2018 CoST Teaching Excellence Merit Award. Dr. Ofori-Boadu received both the 2017 NC A & T - CoST Rookie Research Excellence Award and the 2017 North Carolina A & T State University (NCAT) Rookie Research Excellence Award. Under her mentorship, Dr. Ofori-Boadu's students have presented research posters at various NCAT Undergraduate Research Symposia resulting in her receiving a 2017 Certificate of Recognition for Undergraduate Research Mentoring. In 2016, her publication was recognized by the Built Environment Project and Asset Management Journal as the 2016 Highly Commended Paper. Andrea has served as a reviewer for the National Science Foundation (NSF), Environmental Protection Agency (EPA), and several journals and conferences.

Dr. Ofori-Boadu engages in professional communities to include the American Society for Engineering Education (ASEE), the National Association of Home Builders (NAHB), and the National Association of Women in Construction (NAWIC).

In 2015, Dr. Ofori-Boadu established her STEAM ACTIVATED! program for middle-school girls. She also serves as the Executive Vice-President of Penuel Consult, Incorporated. She is married to Victor Ofori-Boadu and they are blessed with three wonderful children.

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Abstract

Evaluating student success in higher education relies heavily on Grade Point Average (GPA), a measure determined by faculty through formative and summative assessments. Faculty determine these grades throughout the student's academic career. Society often equates higher grades with greater intelligence and engagement, assuming students work independently. Grades are also a means to measure or quantify learning and intellectual progress during students' academic careers. However, when students resort to unsanctioned online resources (UORs) using applications like Chegg, Course Hero, and Slader, the student may obtain good grades, but understanding and learning are grossly sacrificed. This study investigates the performance of 100 engineering students in the gateway course of Mechanical Engineering, specifically Engineering Mechanics-Dynamics. Dynamics is a gateway course in the undergraduate Mechanical Engineering program. Failure to demonstrate proficiency in the basic principles of Dynamics may lead to academic delays and program dropout, with a high attrition rate. The study collected data for three academic semesters using four assessment methods: online homework assessments, in-class proctored tests, an adaptive intelligent engine assessment platform, and in-class proctored final exams. Students can take homework assignments using both platforms from the comfort of their homes. While solutions from UORs were readily available for homework assignments, access to solutions for the adaptive intelligent engine platform was only possible through contract cheating. The analysis of the results through cluster analysis indicates that 29% of the students excelled in all four assessment methods, while 30% performed poorly in all four assessment platforms. The puzzling results are from the remaining 41% of the students who excelled on out-of-class assessments but failed their in-class proctored tests and examinations. The study concludes that cheating and academic dishonesty have negative implications, leading to academic failure, poorly performing students and graduates, and a retrogressing society.

Introduction

Academic integrity violations have serious repercussions. Faculty and students who have violated these guidelines have received harsh penalties. Students can anticipate formal sanctions from the university that could adversely affect their grades and, in some situations, their ability to advance in their academic careers. Despite the severe consequences, students still violate academic honesty. Academic dishonesty has existed for ages, but the recent COVID-19 pandemic and advancements in information technology, including artificial intelligence, have made these unethical activities much more widespread and challenging to curtail [1]. Academics and universities worldwide need help to develop ways to combat plagiarism, and these efforts are hampered by services that provide solutions to assignments for a fee for college students [1]. This type of illicit service is referred to by its official titles as contract cheating or ghostwriting for assessments.

Contract cheating is a problem that can be characterized as a systemic flaw degradation of student integrity standards. Assessments for college students are measures used to evaluate their learning and are thus very important and should not be compromised. These assessments generally have one of three purposes: assessment for learning, assessment of learning, and assessment as learning [2]. In academia, the link between assessment methods and how they impact student learning remains a concern, and variations such as online assessments therein may lead to more concerns. For example, contract cheating has reduced the validity of assessments as a measure of student learning. In addition, it has a wide range of effects on the student, the academic community, the university, and society.

Students who do not use contract cheating services are forced to watch their classmates succeed academically without making the necessary effort or learning anything of value from the experience. Due to the influence of grades on the opportunities accessible to students, this negatively impacts the fair treatment of students. Teaching and learning suffer whether these threats are identified or not. When contract cheating is reported and investigated, significant resources are used that would have been otherwise devoted to teaching and learning. Students perceive the professor as ignorant if cheating goes unnoticed, which gives them the confidence to continue or even upscale. Finally, colleges that decide to look into these violations and pursue legal action may experience lower enrollment and be viewed as too harsh.

In contrast, universities that decide not to look into them may experience a decline in academic standards. The overall implication is that employers must rely on something other than colleges to produce knowledgeable and adaptable graduates for the rapidly evolving work environment. When academic integrity is compromised, there is a risk that students, educators, employers, and the worldwide community will lose faith in educational standards if the root causes are not treated, and control implemented to avoid resurgence.

Technological advancements and the growth of Information Technology companies have significantly transformed how students study and learn in online, hybrid, or onsite environments [3]. Online learning environments have both advantages and disadvantages. A significant challenge is how proper assessments can be conducted fairly. Academic practice is affected significantly by the symbiotic relationship between the increasing number of online examinations and contract cheating services. For instance, controlling the online assessment environment is more challenging than controlling the onsite one. Cheating in a remotely proctored online testing (RPOT) environment is a planned undertaking rather than panic cheating because students complete their exams in isolation in their comfort zone [4]. Cheating is aided by the rapid proliferation of unsanctioned online resources (UORs) [5] such as Chegg, Course Hero, and Slader that offer solutions to several question banks hosted by

textbook vendors, help from friends and associates, or making false claims during the tests [4, 6]. In the case of cheating in RPOT environments, a paid contractor uses remote access software to bypass testing controls and remotely answer test questions for the test taker. Since tests and homework are designed for formative and summative assessment purposes in higher education, their onsite and online integrity must be protected. Finally, proctoring has been used to maintain online testing integrity as in onsite tests.

In this study, we looked at the performance of 100 mechanical engineering students in the Engineering Mechanics-Dynamics course to understand how students perform in UOA and proctored in-person environments. Data was collected over a period of three semesters. This course was chosen for this study because it is a gateway course. It is historically known that engineering students who failed this course experience delays in their academic careers and may even abandon or switch programs. These requirements make this course a good barometer for assessing whether or not students will uphold the values of academic integrity. This was assessed by introducing them to four different assessment methods. In un-proctored online assessment (UOA) environments, students can access online solutions via popular UORs platforms or contract cheating. Ready access to solutions gives every student the freedom to act however they want, especially to maintain their academic integrity or not. In proctored onsite assessments, an instructor monitors students' actions during the assessment duration.

Limitations

Participants in this study included students with impairments who had received letters of accommodation from the Office of Accessibility Resources (OARS). Nevertheless, the study is limited in scope since it did not examine how students with legitimate test anxiety concerns but who were unable to obtain accommodation letters from OARS. The study did not consider the impact of working students, students' socioeconomic background, the effects of parenthood, the effects of pedagogy, and poor metacognition skills on students' performance of academic performance.

Methods

Assessment Design

Realizeit is a cutting-edge learning platform that aims to transform how people learn new information and skills. Realizeit's interactive and engaging material adapts the material to the student's competency level. It provides learners with personalized and dynamic learning experiences through gamification, short video courses, and quizzes. Its adaptive technology enables students to advance comfortably and redo all assignments to improve their grades. Its gamification features encourage them to continue their learning path [11]. The nine quizzes conducted on the platform contributed 25% of the total student score in the study.

Another learning platform that is utilized is called Mastering Engineering. All assessments deployed on Mastering are randomized to ensure students do independent work. We used this platform to deploy nine homework assessments that accounted for 15% of the overall score. This platform allows students to utilize feedback to construct a strategy for transitioning from a state of not knowing to one in which they have mastered their learning goals.

Recycling questions from Realizeit and Mastering platforms constructed in-person tests and final examinations. These questions were adapted for tests and final examination by modifying a combination of the stem's basic parameters, such as units, variables, and solution method. These changes do not affect the difficulty level of the questions, but they prevent students from memorizing solutions to problems and regurgitating the same during tests and examinations. To reduce test anxiety, students were provided with a comprehensive list of equations and diagrams during tests and examinations so that they could focus on presenting solutions based on reasoning from first principles. This same list of equations was available to students to assist with the solution to Realizeit and Mastering problems and also to familiarize students with the equations.

Table 1 summarizes the various assessment types indicating their corresponding frequencies, weights, and whether a given assessment was proctored. The in-person assessments consist of three tests, including one midterm examination and one final examination, each accounting for 30% of the overall score, and these are proctored. The instructor makes numerous copies of tests and final exams with different questions during these assessments. Students were spaced out during testing, and people sitting adjacent to one another were given different test sheets. The degree of difficulty of the questions is consistent across all four-assessment types. Blackboard is used to compile the grades across assessment types. The final cumulative weighted average is calculated proportionately according to the weighing scheme shown in Table 1.

Table 1: Assessment Types, Frequencies, and their weights

Assessment types	**Number of Assessments**	**Weights (%)**	**Assessment Proctored**
Realizeit: Adaptive Assessment	9	25	No
Mastering: Online Homework (HW)	8	15	No
In-person test	3	30	Yes
In-person Final Examination	1	30	Yes

Clustering Analysis

Clustering helps to separate the data sets into a certain number of clusters such that the data points fitting into a cluster have similar features. Clusters are made from grouping data points such that the distance between the data points within the clusters is minimal. Clustering is done to separate the groups with similar characteristics. Identifying such clusters leads to subdividing data points into many different groups. Clustering is considered unsupervised learning because clusters are recognized from the data set instead of known target classes.

K-means Clustering

Clusters could be formed by different clustering algorithms such as k-Means clustering, hierarchical clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). Each of these different clustering algorithms produces different types of clusters. K-means clustering is a popular and straightforward method to separate a dataset into a set of k groups or clusters. It starts by selecting random K cluster centers, and the data points are formed into one of the k-cluster using the cluster's centroid, and each cluster is acknowledged by its centroid. The centroid is a location representing the center of the cluster. Then the cluster centers are re-calculated as the centroids of the recently formed clusters. The data points are re-assigned to the closest cluster centers we re-calculated. The process of assigning data points to the cluster centers and re-calculating the centroid is repeated until the cluster centers stop moving. The aim is to lessen the sum of distances between the instances and the cluster centroid to identify the correct group each instance should belong [12]. The most common approaches for generating the distance matrix are Euclidean and Manhattan distances. Euclidean distance is generally considered to determine the distance between each data object and the centroids [13]. The Euclidean distance between one vector x = $(x_1, x_2, \ldots, x_n)$ and another vector y= $(y_1, y_2, \ldots y_n)$, The Euclidean distance $d_{euc}(x_i, y_i)$ can be obtained as follow:

Euclidean distance:

$$d_{euc}(x_i, y_i) = \left[\sum_{i=1}^{n} (x_i - y_i)^2\right]^{1/2}$$

The Manhattan distance is the summation of absolute differences. The Manhattan distance $d_{man}(x_i, y_i)$ can be obtained as follow:

Manhattan distance:

$$d_{man}(x_i, y_i) = \sum_{i=1}^{n} |(x_i + y_i)|$$

For this study, we used the Euclidean distance since minimizing the distance is equivalent to minimizing the square of the distance.

Clusters formed by k-Means clustering tend to be similar in size. Moreover, clusters are convex-shaped, and since k-Means clusters are formed using the centroid of the cluster, it's sensitive to outliers.

Using the minimal distances between the points in the dataset indicates that data points have been separated through the least variance within them to form the most compact clusters possible. Therefore, no other iteration would be needed to lower the average distance between the centroids and the data points found within them.

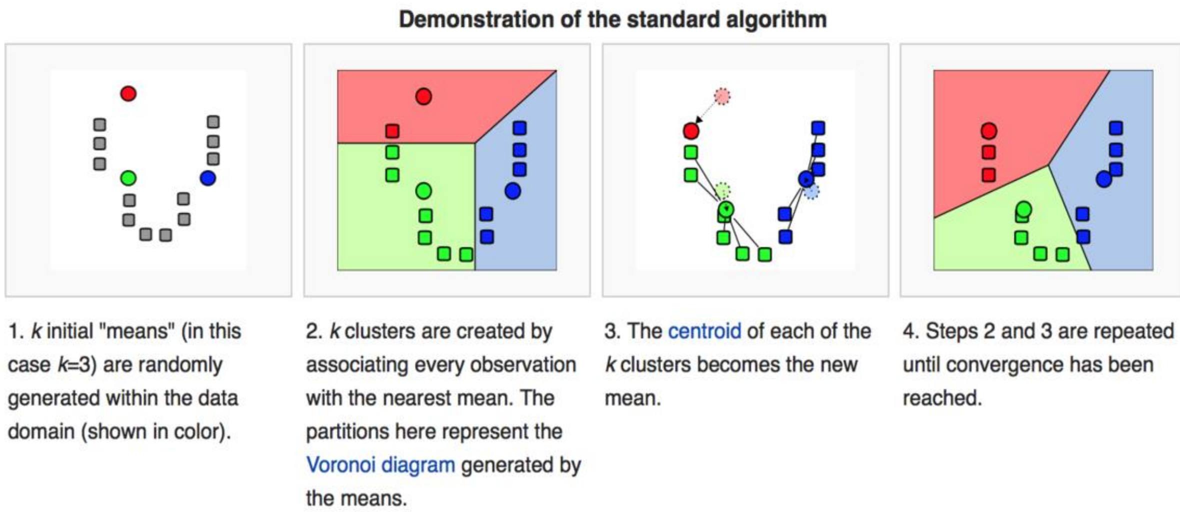

Figure 1: A graphical look at k-means clustering [14]

K-Means clustering is a simple, fast, and robust method that uses data sets distinct and well separated from each other linearly to produce reliable results. It is usually best when the number of cluster centers is defined. However, when the data is noisy or contains outliers, there are heavily overlapping data, or the Euclidean distance does not measure the underlying factors well, K-Means clustering may perform poorly.

Determining the Optimal Number of Clusters

The optimal number of clusters refers to the most suitable number of groupings that accurately represents the underlying patterns in a dataset. The number of clusters specified can significantly impact the results of clustering. Therefore, it is crucial to offer expert guidance on determining the appropriate number of clusters to obtain accurate clustering results [15]. There are several methods available in literature to identify the optimal number of clusters, such as the Silhouette method, the Gap statistic, and the elbow method. The Silhouette index, introduced by Kaufman and Rousseeuw [16], graphically represents how well each object is classified in each clustering output. The silhouette value assesses how similar a point is to its cluster in comparison to other clusters. Tibshirani et al. [17] proposed the gap statistic approach in 2001 to estimate the number of clusters in a dataset. The elbow method, on the other hand, is probably the most well-known method for determining the optimal number of clusters. It calculates the Sum of Squared Errors (SSE) within clusters for various k values and selects the k value for which SSE initially starts to decrease. This point is evident as an elbow in the plot of Total within SSE-versus-k. It is essential to provide expert guidance in defining the number of clusters to obtain accurate clustering results. For this study, we utilized the elbow method.

The k-means clustering method was used to cluster assessment data into groups based on their homework, Realizeit, test, and final examination scores. K = 3 was observed as the optimal number of clusters.

Results and Discussion

The overall student performance across the various assessments is shown in the parallel boxplots of Figure 2.

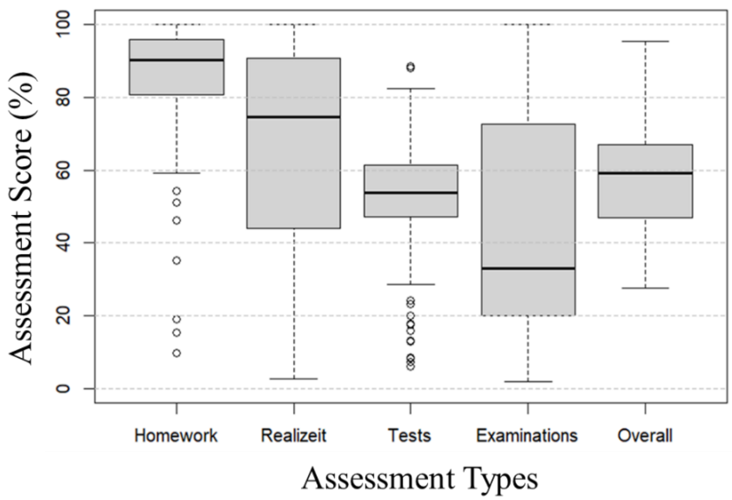

Figure 2: Boxplot summarizing student performance across assessments.

Each boxplot shows the five population statistics - the minimum, the lower quartile, the median, the upper quartile, and the maximum. Except for the test, the rest of the assessments are heavily skewed. HW and Realizeit assessments are skewed to the left, while the final examination is skewed to the right. None of the data are from a normal population. The horizontal black line indicates the average scores. Passing Dynamics requires a letter grade of a D, translating into a minimum 60% score. The overall average score is slightly below 60%, while HW and Realizeit scores are above 60%. However, tests and examination scores are well below the 60% passing requirement.

The elbow approach was used to calculate the optimum number of clusters for the dataset. Figure 3 shows a scatter plot of the Within-Cluster-Sum-of-Squared-Errors (WSS) with cluster size, where the optimal cluster size is chosen as the value of K at which the rate of change in WSS first begins to decrease. It is clear from the illustration that the elbow transforms when K = 3 or 4. Therefore, we chose K to be 3 for this investigation.

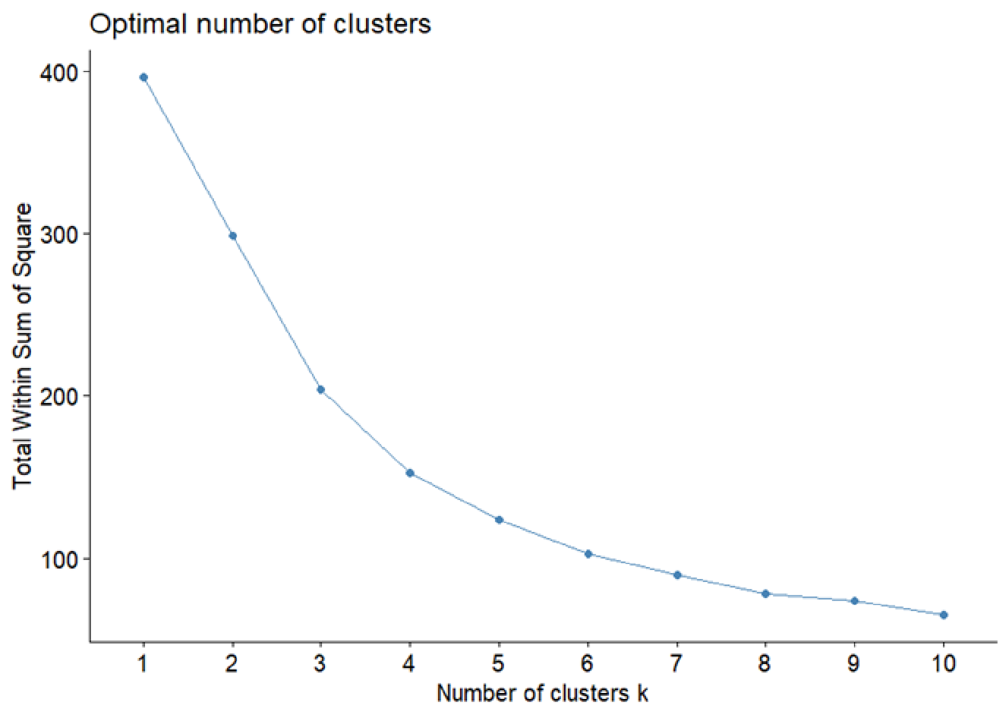

Figure 3: Determination of the optimal number of clusters

Results from the cluster analysis are summarized in Table 2. The Within Assessment Performance is calculated by taking the average scores for each cluster within an assessment. The average performance for each cluster is the weighted average of scores across each cluster.

Table 2: Result from the cluster analysis

Within Assessments Performance (%)					**Average Performance (%)**
Cluster	**HW**	**Realizeit**	**Tests**	**Exams**	**Combined Assessments**
1	89.05	70.83	61.69	78.96	73.26
2	71.37	36.88	32.24	33.96	39.79
3	91.44	85.91	56.89	23.73	59.38

Conclusion and Recommendations

The issue of cheating among students has significant implications that affect everyone. Beyond compromising academic integrity, it threatens national security and undermines the nation's position as a superpower. Unprepared graduates entering the workforce leave the United States vulnerable, a concern that all stakeholders, including parents, administrators, faculty, and students, must address.

Flower Darby et al. (2020) [18] proposed a straightforward and efficient solution to the problem of students cheating online. The authors suggested that high-stakes exams be broken up into a series of smaller weekly tests to relieve the stress that students experience and, as a result, lessen the allure for them to engage in dishonest behavior. In addition, she suggested that teachers should require students to explain the steps they took to solve a problem. This approach would make it more difficult for students to locate solutions online.

Williamson M. H. (2018) [19] suggests creating test questions solely from information found in the textbook rather than from test banks or publisher materials and implementing quiz restrictions that prevent students from seeing the next question or backtracking. In addition, Williamson recommends that teachers provide students with questions in the form of brief essays to determine their understanding of the topic.

Noorbehbahani et al. (2022) [20] present a variety of strategies to prevent students from cheating during examinations. One of these strategies is using cheat-resistant technology, such as browser tab locks or wireless jammers. They also recommend a strategy called think-aloud request, in which students are prompted to record their responses to a question during the test verbally. They also encourage teachers to prepare a large pool of questions to avoid question repetition.

In examining the performance of 100 students across three clusters, we observed from Table 2 above that cluster 1, comprising 29% of the students, performed well. In contrast, cluster 2, representing 30% of the students, struggled on all assessments except homework. However, the most concerning result was observed in cluster 3, which accounted for 41% of the total. These students performed exceptionally well on out-of-class assessments but struggled on in-class proctored tests and examinations. Questions in the in-person tests and final examinations were pooled from Mastering and Realizeit platforms, with units and variables changed. These students, in proctored environments, could not solve the same problems they performed exceptionally in un-proctored environments. This puzzling outcome suggests that many students may be engaging in dishonest practices such as UORs and contract cheating, which can ultimately lead to academic failure. It is, therefore, imperative to address the root causes of cheating to uphold academic integrity and promote a culture of honesty and excellence.

The following are some suggested guiding rules:

1. Universities must have a well-documented policy on cheating, which should be disseminated widely among students, parents, faculty, and administrators. While repercussions should be firm, they need not be overly harsh, and offenders should be provided with multiple opportunities to rectify their actions.

2. Prospective students must complete an on-demand, self-paced course on policy regarding cheating, ethical behavior, and integrity in assessment, whether proctored or not, as a prerequisite for admission.

3. Orientation seminars should be organized for university, college, and department freshmen, with instructors emphasizing the repercussions of cheating on the first day of class.

4. Assessments with a high risk of cheating should be low stakes, but students must understand that cheating is not worth the effort, despite the low stakes.
5. Instead of individual instructors setting questions for high-stakes assessments, a minimum of three faculty members with knowledge of the subject matter should be involved.
6. Technology can be a double-edged sword that can work for or against us. With increasing enrollment, grading written responses to assessments has become more difficult for instructors. However, technologies such as browser lock-down and webcam monitoring cause more problems than they solve. The university should have dedicated test centers with computers that provide minimal functionality to students. This environment should be controlled and proctored.

The recommendations are undeniably valuable, but more is needed to mitigate the complex nature of cheating and its danger to national security. In order to combat this risk effectively, it is crucial to synergize efforts at the national, state, and institutional levels. This strategy calls for a concerted and collaborative approach that harnesses the strengths and resources of various stakeholders.

To facilitate more informed decision-making and policy development, the authors propose conducting a thorough literature review to compile a comprehensive review paper on cheating. This paper will provide a broad and nuanced understanding of the factors that drive cheating and the various strategies and interventions that have proven effective in curbing it. By drawing on a wide range of disciplinary perspectives and empirical evidence, this review paper would provide a solid foundation for policymakers and practitioners at all levels to develop evidence-based interventions that target the root causes of cheating. With a robust evidence base and collective action, we can safeguard the integrity of our institutions and protect our nation's security.

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