Nonparametric Analysis of the Effect of Knowledge Integration Activities on Third-Year Undergraduate Performance

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Abstract*—*Contribution: **This article presents quantitative support that the changes implemented as part of Colorado State University's (CSU's) Revolutionizing Engineering Departments (REDs) grant produce statistically significant positive change through a series of nonparametric analysis techniques. Additionally, the set of nonparametric analysis techniques provides a novel approach to quantitatively analyzing student data after significant pedagogical changes are made to the undergraduate curriculum.**

Background: **As part of the grant, a series of significant pedagogical changes were made to the electrical and computer engineering (ECE) undergraduate curriculum. A large portion of these changes relates to knowledge integration techniques, which are used to highlighting the intricate relationships between the three topics of electronics, signals and systems, and electromagnetics. This article presents an analysis of the outcomes that are in part due to these changes.**

Intended Outcomes: **As a result of the grant and the associated curriculum changes, it was anticipated that the cumulative in-major grade point average for third-year students would increase. It was also anticipated that the in-major intercourse grades would be more positively correlated. The analysis techniques that were used provide novel examples of applications to student data.**

Application Design: **The implemented changes described in this article directly follow from the goals of the National Science Foundation's RED program.**

Findings: **Three nonparametric analysis techniques are performed on a collection of data from ECE undergraduates that was collected over 20 years. It is shown that the intertopical correlations between courses increase immediately following the implementation of the intervention discussed in this article, and statistically, significant evidence is presented supporting that the distribution of grades has positively changed following the intervention.**

***Index Terms*—Computer engineering, computer science, correlation, electrical engineering, knowledge integration (KI), Kolmogorov–Smirnov (KS) distance, National Science Foundation (NSF), principal component analysis (PCA), Revolutionizing Engineering Department (RED).**

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I. Introduction

THE ELECTRICAL and Computer Engineering (ECE) Department at Colorado State University (CSU) received a five-year Revolutionizing Engineering Departments (REDs) grant from the National Science Foundation (NSF). The RED grant promotes significant sustainable changes that are required to overcome longstanding issues in the undergraduate curriculum. Changes proposed to CSU's curriculum center around throwing out the course-centric teaching model through a series of pedagogical and organizational changes, specifically during the second and third years [1].

These changes are motivated by the following. Students who have the desire and aptitude to excel as an engineer might not be engaged by the current curricula due to potentially not appreciating the relevance of the topics being taught and are consequently abandoning the discipline. This has been a particularly harsh reality for ECE students who enter the middle second and third years of the core undergraduate program when an accelerated number of new concepts is introduced. Furthermore, undergraduate engineering students who do eventually graduate might not fully grasp their role as an engineer, or the skills and expectations required of them when applying for jobs [2].

The courses taught during the third year cover the topics of electronics, signals and systems, and electromagnetics, and traditionally, these three topics are taught in parallel with little interaction and explanation of the dependencies between them. The lack of integration between the three topics has falsely motivated students to believe that a successful electrical and computer engineer only has to be competent in a single one of these topics. These changes are poised to remove this intertopical isolation by implementing learning studio modules (LSMs) and knowledge integration (KI) activities [3].

LSMs provide a mechanism for examining third-year content at a fine-grained level. Through each LSM, material is presented in a cohesive manner so that students can see how anchoring concepts from each topic are interrelated and critical to understanding the big picture.

Each of the seven third-year ECE courses in the technical core (all 300-level courses noted in Table I) was analyzed by multifaceted faculty teams and had their course content segmented into LSMs. Each LSM is a self-contained set of materials, presented over a two-week period, that covers one overarching concept and the associated subtopics that compose

it. One example of an LSM for the signals and systems topic is as follows. The overarching concept is linear time-invariant (LTI) systems, with the subtopics of continuous- and discrete-time systems, linearity and time invariance, discrete-time LTI systems and the convolution sum, continuous-time LTI systems and the convolution integral, and properties of LTI systems [1], [2].[1]

The topics and presentation schedule of the LSMs were coordinated across the three core topics by faculty teams to ensure the optimal ordering of the content. After each series of two LSMs, students are brought together with the faculty to participate in KI activities that further connect the ideas presented in the previous LSMs.

The KI activities are implemented such that all the faculty and students from the third year come together in one room to participate in interactive, team-based learning exercises that illustrate how LSM concepts are highly connected and dependent on each other to ensure the correct functionality of a complex system [2], [4].

The students take part in hands-on KI activities, which are completed as lab-like exercises. To prepare for KI activities, students are asked to complete some minor research and high-level system design that does not require intricate knowledge of the underlying component-level blocks that compose the system. Part of the KI prework requires students to make a list of all possible concepts and topics from the previous LSMs that are relevant to the problem.

One example of a KI activity is designing a power supply for a cell phone. The design problem asks the students to design a bridge rectifier circuit with a specific output voltage and constraints on the voltage ripple. Additional constraints follow in the form of limited component choice and a 60-Hz AC power source. Students are asked to discuss the charging and discharging actions of a capacitor on the output stage of the power supply in terms of the electric field within the capacitor and additionally perform some analysis of the filter that is created by their power supply. As such, this KI activity requires students to use concepts from LSMs which would typically come from different courses [1].

In addition to the LSMs and KI implementation, CSU's implementation of the RED grant introduces three common threads throughout the undergraduate curriculum. The first thread is *creativity*, which provides the students with experience exploring the creative side of engineering through course projects from freshmen to senior year. The second thread is *professionalism*, which teaches students the skills required to navigate the work environment through regular presentations, and interactions with "engineers in residence" [5]. The third thread is *foundations*, which ensures the students are presented with the fundamental mathematics and science prerequisite knowledge in a manner that is consistent both topically and temporally with the ECE curriculum. CSU's ECE and mathematics departments have worked together to provide a cohesive learning experience between the calculus series and ECE courses as a part of the grant [6].

[1]The complete set of LSMs and KIs is available at: https://www.engr.colostate.edu/ece/red/3rd_year_curriculum.php.

Since the implementation of the RED grant, the traditional notion of homework and tests still apply, but students are now also evaluated on their performance and participation in the KI activities. Additionally, all students take a set of concept inventories at the beginning of their senior year to measure the information retention rate in each of the topics.

There has been a mix of instruction methods since the RED grant implementation. Most notably, a collection of flipped and partially flipped classrooms have been used with the coordination of learning assistants. Learning assistants are students whom have previously done well in a course and are seeking to help students strengthen their learning strategies and master course material. They attend the course which they are supporting and provide real-time assistance for solving problems in the case of flipped classrooms.

Additionally, Notaroš *et al.* [7] described an integrated approach to electrical engineering education that incorporates the computer-assisted MATLAB-based instruction and learning into the junior-level electromagnetics course and newly created LSMs that was implemented as part of the RED grant.

The purpose of this article is to quantify the differences between the performance in the third-year ECE courses for the students who attended CSU prior to the implementation of the KI activities and the students who have attended CSU since the KI activities have been implemented. In the remainder of this article, these two different time periods/groups will be referred to as the pre-KI years/students and the KI years/students, respectively. The work presented in this article builds on research that studied the Spearman correlation coefficient and performed a principal component analysis (PCA) on the grade point average (GPA) from third-year ECE courses to help identify meaningful relationships between those courses [8]. In this article, the previous research is extended by examining a larger set of courses and by comparing two sets of students, the pre-KI and KI groups, through the two aforementioned methods and the use of the two-sample Kolmogorov–Smirnov (KS) test. The three main analysis techniques used in this article (Spearman correlation, PCA, and KS test) are examples of *nonparametric analysis techniques*, which make no assumption about the underlying distribution of the data. This implies that the results are a consequence of information that exists within the data, and not due to a (likely incorrect) model assumption for the distribution of the data.

The significant contributions of this article come in the form of quantifying the changes of the KI activities that were implemented as a part of the NSF RED grant, using the aforementioned nonparametric analysis techniques. The work presented in this article addresses an open research question in undergraduate engineering education, which is how to measure a student's ability to integrate content knowledge from different courses and apply it to new problems. Specifically, two of the original outcomes proposed by CSU's RED implementation have been realized. The first is that the three topics presented in the third-year courses are more highly correlated for the KI students, indicating that those students see the intertopical relationships more clearly than their pre-KI counterparts. The second is that there exists a significant positive

change in the distribution of the ECE GPA in the third year shown using the two-sample KS test.

The remainder of this article is presented in the following format. The literature review section discusses intervention-based methods for improving student performance as well as similar research that is conducted on identifying relationships between prerequisite and requisite courses. The data section presents the data set that was used in the analysis, including the decisions that were made to select a subset of the entire data set for processing. The analysis method section describes the three different methods that were used in this article, including an overview of the Spearman correlation coefficient, PCA, and an explanation of the KS distance and the nonparametric hypothesis test based on the KS distance. The results and discussion section presents the relationships that were found within the data using the aforementioned analysis methods.

II. Literature Review

The idea of KI is central to CSU's implementation of the RED grant. KI within engineering education has a long history with a growing body of literature that exemplifies the positive impacts to undergraduate learning [9]–[11]. Not all KI implementations, including those that provide a similar increase in performance indicators that are presented in this article, are based on RED grants. Olin College of Engineering provides one example of a truly integrated academic experience by having instructors from multiple disciplines working together to engage students in projects modeled after real-world engineering problems [12]. The RED grant implementation at CSU is largely inspired by Olin's approach, but was designed to overcome a limitation of their implementation. In particular, Olin's implementation can be challenging to reproduce within the barriers of a typical public university. As such, CSU borrows from the main components of Olin's philosophy and modifies it in a way that can be realized and sustained within the constraints of many higher education organizations. Readers interested in learning more about the RED grant implementation at CSU, and what limitations in current pedagogical methodologies it aims to solve, are referred to [1].

Methods for quantifying impact from intervention-based changes in education have been examined in [13]. Specifically, the authors proposed the use of linear regression models that can identify and control for student ability and preparation levels in science, technology, engineering, and mathematics (STEMs) courses to quantify the change between preintervention and postintervention test performance. In line with the authors' concern of comparing similar students, the research performed for this article used the two-sample KS test to ensure that the comparison groups are drawn from the same population prior to evaluating student performance due to the intervention.

Simpson and Fernandez performed research on a data set that is similar to the one presented in this article to identify if strong correlations exist between students' grades during their early semesters and their corresponding performance in mid-level engineering courses. Their work is consistent with the data presented here for the pre-KI group of students [14]. In their work, they used a linear correlation instead of a monotonic correlation, as used in this article. The grade data used in this article exhibit monotonic trends and thus using a monotonic correlation overcomes the analysis limitations that a linear correlation negatively imposes on the data.

Research in identifying relationships between a student's ability to graduate from university and their performance in both high school and university using monotonic associations have also been performed in [15]. The analysis in this article uses similar methods, but identifies relationships between the performance in core topical courses before and after a major pedagogical change.

The data used in this article have been collected, in part, for the inclusion in the multiple-institution database for investigating engineering longitudinal development (MIDFIELD) data set. Research conducted on larger sets of the MIDFIELD data include the identification of relationships between gender, race, and trajectory paths of engineering students [16], but does not analyze the changes in student performance resulting from intervention or pedagogical changes.

III. Data

The data that are analyzed in this article come solely from CSU undergraduate students, but are also available as part of the MIDFIELD data set. As part of the MIDFIELD data collection, anonymized student records are kept for every semester that students are enrolled and include information, such as individual course grades and cumulative GPA as well as high-school academic records. More details about what data are collected for the MIDFIELD data set can be found at [17].

Data records from the ECE undergraduate program, collected over the past 27 years, were used for this analysis. The full data set consists of over 2800 individual student records, but only the student records with a complete set of grades in all first-, second-, and third-year required ECE courses were analyzed. This reduced the size of the data set that was used in the analysis to 751 students. A more detailed description of the contents of the data set is given in [8].

The data were partitioned into two groups. The first group consists of all students who took the third-year courses prior to the implementation of the KI activities (pre-KI students), and the second group consists of all students who took the third-year courses after the implementation of the KI activities (KI students). The distribution of cumulative GPAs can be seen in Fig. 1 for the two groups at the end of the second and third years. To ensure that the two groups of data could be compared appropriately, the two-sample KS test was applied to show that the distribution of the cumulative GPA for both groups at the end of their second year was statistically similar. The two-sample KS test was also applied to identify that the ECE GPA at the end of the second year was statistically similar for both groups. This showed that the students from the first and second groups are drawn from the same population at the end of their second year.

The students who had a complete set of grades in all first-, second-, and third-year required ECE courses, and subsequently participated in the study, account for $27.8 \pm 5\%$ of the

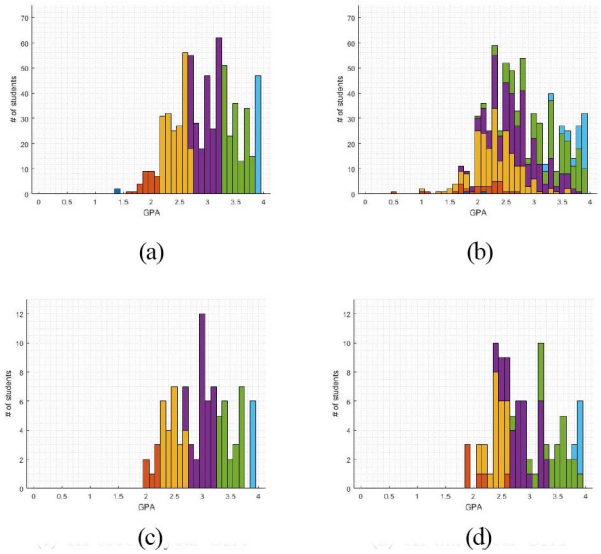


Fig. 1. Distributions of the cumulative GPA for the end of the second and third years. The students were designated to one of five groups at the end of the second year, as denoted by the different colors in each plot, depending on how far their GPA was from the mean. Each group was tracked through the end of the third year to observe the change in the distribution of groups between the second and third years. (a) Pre-KI second-year GPA. (b) Pre-KI third-year GPA. (c) KI second-year GPA. (d) KI third-year GPA.

total number of ECE students that were admitted each year. This is illustrated in Fig. 2. The number of pre-KI students that are included in the study depicted by red, the number of KI students that are included in the study depicted in yellow, and the number of students who are not included in the study but were ECE majors depicted in blue. The more recent years (2010+) have both a mixture of pre-KI and KI students. This is due to some of the earlier admitted students not progressing to the junior year by the time the changes started, and some of the later admitted students being transfer students and thus entering during their junior year. For the 751 students that are included in the study, the mean cumulative GPA of each year's cohort is within two standard deviations of the mean cumulative GPA calculated over all years (for all 751 students).[2] The same is true for the in-major ECE GPA. As with all student bodies, there have been cohorts that perform better than others, been composed of slightly different characteristics (e.g., female/male ratio, transfer/traditional students ratio, etc.), but there is no significant difference throughout the data-collection period. This shows that there is no evolutionary differences, over the data-collection period, in the cumulative and in-major student performance, the ratio of students who are included into the study to those who are not, and the general student profile (gender, transfer/nontransfer, etc.).

The courses that were examined throughout this article are listed in Table I and include the entire set of first-, second-, and third-year ECE courses, the calculus series and introduction to differential equations, a number of introductory computer science classes, and a select number of nontechnical courses.

[2]The results for the 2005 cohort are slightly below the two standard deviation mark. This is likely attributed to the economic crisis that occurred in 2008, the year that cohort would have started their third-year studies.

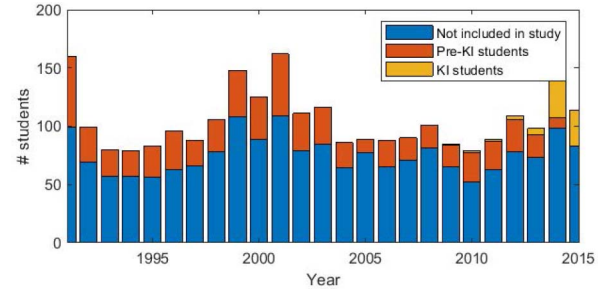


Fig. 2. Number of ECE students per admission year, split into three groups: pre-KI, KI, and students who did not participate in the study. Included students account for $27.8 \pm 5\%$ of total ECE students year by year.

The undergraduate ECE curriculum at CSU is, and has been for the data-collection period, one that presents the fundamentals of ECE principles in the areas of electromagnetics, signals and systems, and electronics. The fundamental theoretical approach has remained consistent in these areas during the data-collection period, and the availability and content of each of the core ECE courses (first-, second-, and third-year courses referred to in Table I) have remained consistent throughout. Many of the ECE courses have had a small collection (two or three) of professors providing the layout, content, and presentation for a sustained amount of time. This has helped to maintain the consistency within courses over the years in which the data have been collected. No significant pedagogical changes have been made over the duration of the data collection, with the exception of the RED grant.

IV. Analysis Methods

A. Methods Overview

Three different nonparametric analysis methods are used in this article. The first method used is the Spearman correlation coefficient [18], which helps identify monotonic relationships between two variables. The Spearman correlation coefficient was chosen in favor of the more commonly used Pearson correlation coefficient. This is because the understanding of the linear relationships between the performance in each course is not desired. More generally, it is desired to understand whether students will perform better in one course given that they perform better in another course. The second method used is PCA, which helps identify the amount of variance in the performance that is explained by each individual course. In particular, PCA reveals trends in the data that are not easily observable in the raw data [19]. The third method is the two-sample KS nonparametric hypothesis test for testing if two samples are drawn from the same population [20]. The KS test is used as it avoids placing assumptions on the underlying distribution of the student GPAs.

For all three methods of analysis, the data were split into two disjoint sets. The first set of data is composed of $N_{\text{pre-KI}} = 659$ pre-KI students, while the second set of data is composed of $N_{\text{KI}} = 92$ KI students. For the correlation analysis and PCA, a column vector $\mathbf{x}_i \in \mathbb{R}^N$ was constructed with data from the ith course where the kth component of $\mathbf{x}_i$ represents the grade that the kth student attained in course i. For the pre-KI group,

TABLE I
COURSES EXAMINED IN THIS ARTICLE. ONE NONTECHNICAL GROUP OF COURSES ALONG WITH A MATHEMATICS, CS, AND ECE GROUP

Course Number	Course Name
CO150	College Composition
ECON202	Principles of Microeconomics
MU100	Music Appreciation
MATH160	Calculus for Physical Scientists I
MATH161	Calculus for Physical Scientists II
MATH229	Matrices and Linear Equations
MATH261	Calculus for Physical Scientists III
MATH340	Introduction to Ordinary Differential Equations
CS155	Introduction to Unix
CS156	Introduction to C Programming I
CS157	Introduction to C Programming II
CS160	Foundations in Programming
CS161	Object Oriented Problem Solving
CS200	Algorithms and Data Structures
ECE102	Digital Circuit Logic
ECE103	DC Circuit Analysis
ECE202	Circuit Theory Applications
ECE251	Introduction to Microprocessors
ECE303	Introduction to Communication Principles
ECE311	Linear Systems Analysis I
ECE312	Linear Systems Analysis II
ECE331	Electronics Principles I
ECE332	Electronics Principles II
ECE341	Electromagnetic Fields I
ECE342	Electromagnetic Fields II

$N = N_{\text{pre-KI}}$, and $N = N_{\text{KI}}$ for the KI group. Each $\mathbf{x}_i$ was normalized by taking its z-score, and a data matrix containing all normalized $\mathbf{x}_i$s was formed such that $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_M]$. In the case of the correlation analysis, $M = 26$ with $\mathbf{x}_1$ through $\mathbf{x}_{25}$ representing all of the courses from Table I and $\mathbf{x}_{26}$ representing the cumulative GPA as it is desired to examine the associations between courses but also between courses and the cumulative GPA. In the case of the PCA, $M = 11$ representing only the ECE courses. The KS test operated on histograms generated from the cumulative and ECE GPAs at the end of the second and third years, for both student groups.

B. Spearman Correlation Coefficient

The Spearman correlation coefficient ρ is a measure of monotonicity between variables $\mathbf{x}_i$ and $\mathbf{x}_j$, and is used in favor of the Pearson correlation coefficient that measures linearity between variables [18]. This is because the relationship between courses has shown itself to be of a monotonic nature. The Spearman correlation operates on *ranked variables*, and an example of how to generate the ranked variables as well as how to calculate the correlation coefficient can be found in [8].

C. Principal Component Analysis

PCA is a linear orthogonal transformation used in many applications, but primarily variance-preserving dimensionality reduction as well as the explanation of the covariance structure that exists within a data set [19]. PCA is used to identify the linear relationship between the overall ECE GPA and the individual ECE courses. A mathematical description of PCA and its implementation relating to this analysis are available in [8].

D. Kolmogorov–Smirnov Test

The KS distance D_{KS} is a statistic that quantifies the distance between two empirical distribution functions and is the maximum of the pointwise distances between two empirical distributions, F_1 and F_2, defined mathematically as

$$D_{\text{KS}} = \sup_x |F_1(x) - F_2(x)|. \tag{1}$$

The KS test is a nonparametric hypothesis test that uses the KS distance between two distributions to either accept or reject the null hypothesis that the samples belonging to the two distributions are drawn from the same population [20]. The null hypothesis is rejected at a level α if $D_{\text{KS}} > c(\alpha)\sqrt{(n+m)/(\text{nm})}$, where n and m are the number of samples used to generate distributions F_1 and F_2, respectively. The value of $c(\alpha)$ can be obtained from a look-up table such as the one presented in [21].

V. RESULTS AND DISCUSSION

A. Results Overview

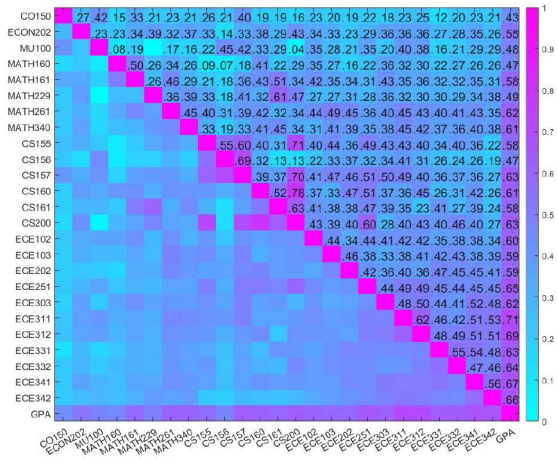
Presented in this section are the results that help explain relationships between the performance in individual courses, as well as relationships between these courses and the overall GPA. The correlations between courses and GPA are discussed, and an analysis of the principal component (PC) that explains the largest amount of variance in the data set is provided. This is done for both the pre-KI and KI groups, and the results from both groups are compared to show the change under the RED grant.

B. Spearman Correlation Coefficient

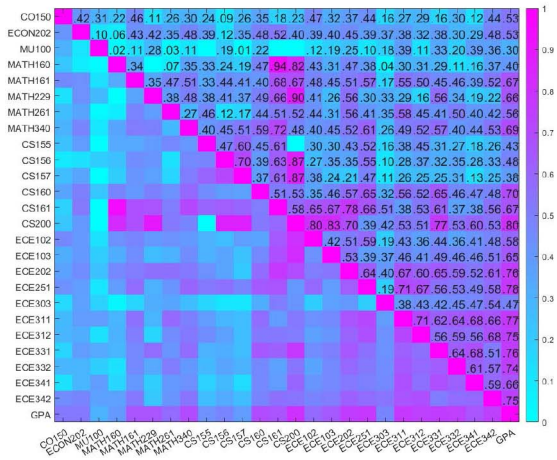
The analysis of correlation coefficients was performed on the entire course list as described in Table I for both pre-KI and KI years, and then compared. A graphical representation of the correlation coefficients between courses is presented in Fig. 3(a) and (b) for the pre-KI and KI years, respectively, but only the analysis of the coefficients for the third-year ECE courses is provided.

The highest correlations, with $\rho \geq 0.59$, exist between the cumulative GPA and each individual course for the pre-KI years. This indicates a moderately strong relationship between the performance in each course and the overall performance of the students. The second highest correlations exist between the prerequisite courses and their requisite counterparts with all values of $\rho \geq 0.55$. This indicates that the performance in the prerequisite course is a moderately strong indicator of performance in the requisite course. This also exemplifies that the most helpful prior course for each second semester third-year course is just the first semester offering within the same topic.

The highest correlations that exist for any one course in the KI years is, again, between that course and the cumulative GPA with $\rho \geq 0.66$. This indicates a strong relationship between the performance in each course and the overall



(a)



(b)

Fig. 3. Correlation values between various technical and nontechnical courses for pre-KI implementation and KI implementation years. Each cell is annotated with the correlation coefficient and the cell is colorized to reflect that value. Empty cells in the upper triangle indicate that there was insufficient information to confidently calculate the correlation coefficient. All values presented are statistically significant with $p < 0.0001$. (a) Pre-KI years. (b) KI years.

performance of the students. The KI student's intertopical correlations change when compared to the pre-KI years. Specifically, the second highest correlations no longer exist between the prerequisite courses and their requisite counterparts except in the case of the signals and systems sequence, ECE311 and ECE312. This shows that the students are thinking of the three topics presented in the third year in a more unified manner, rather than just three independent topics. It should be noted that *all* of the correlation coefficients are higher for the KI years than for the pre-KI years in the third-year courses from the three main topics.

Additionally, the average change in correlation coefficients for intercourse (pairwise between the third-year courses, not including GPA), and course-to-GPA (between individual third-year courses and GPA) was compared. This was accomplished by considering correlation coefficients involving the third-year ECE courses and then calculating the mean of the differences between the corresponding pre- and post-KI correlation coefficients. An average increase of 0.076 for the intercourse set of coefficients is seen, whereas an average increase of 0.05 for the course-to-GPA set is seen. The change in correlation coefficients for the intercourse set is 50% greater than that of the course-to-GPA set, indicating that the connections between courses grew to a greater extent than the connections between the courses and overall performance. This further supports the following: that students are seeing the connection between the three main topical areas, electromagnetics, signals and systems, and electronics, and that there is a greater change in their individual course performance due to a change in other courses than a change in GPA.

The correlations between the calculus courses, from MATH161 forward (see Table I), and all of the ECE courses are greater[3] for KI students than for pre-KI students. This could be a consequence of the foundation's thread, and specifically the work that has been done between the ECE and mathematics departments as part of the implementation of the RED grant.

C. Principal Component Analysis

Two different sets of data were analyzed using PCA. The first set is composed of first-, second-, and third-year ECE course data. Although the first- and second-year courses are not directly involved in the KIs, these courses provide the prerequisite knowledge that is required for the third-year courses, which is also the knowledge that supports the KIs. It is worth highlighting the effect that the RED grant and KIs have on the entirety of the core ECE courses, first- and second-year courses included. The second set is composed of third-year ECE course data. The PCA on the second set of data shows the effect that the RED grant and KIs have on just the third-year courses.

Examining the results of the PCA on the first-, second-, and third-year ECE courses, the first PC captures 54.53% of the variance described in the data set in the pre-KI years and 47.86% in the KI years. The first PCs and the percentage of total variance explained can be seen in Table II. The coefficients of the first PCs are all within a small distance of each other across all courses, indicating that there is an apparent relationship between the overall performance of a student and their performance in individual courses.

A graph is used to help illustrate the connection between the cumulative GPA and the first PC. Fig. 4 contains the cumulative GPAs plotted against the first PC and the associated correlation coefficient. The correlation coefficient was found to be $\rho = 0.999$ for the pre-KI students with $p \ll 0.0001$. This result is in line with results from Johnson and Kuennen [22], which showed that among many factors the GPA accounts for 40.5% of the total influence on the course outcome. The correlation coefficient for the KI students is $\rho = 0.997$, again with $p \ll 0.0001$. This indicates a very strong, almost perfect, positive correlation between the two, and shows that the first PC is effectively a scaled and shifted version of the cumulative

[3]There is one exception, the correlation between MATH261 and ECE341.

TABLE II
FIRST PCS AND THEIR PERCENT OF TOTAL VARIANCE EXPLAINED FOR FIRST-, SECOND-, AND THIRD-YEAR DATA

	Course	$PC1_{pre\text{-}KI}$	$PC1_{KI}$
Year 1 and 2	ECE102	0.2836	0.2736
	ECE103	0.2838	0.1914
	ECE202	0.2784	0.3394
	ECE251	0.2997	0.3364
	ECE303	0.2768	0.2209
Year 3	ECE311	0.3280	0.3312
	ECE312	0.3273	0.3961
	ECE331	0.3314	0.3001
	ECE332	0.3195	0.2750
	ECE341	0.2987	0.3355
	ECE342	0.2815	0.2581
% of Total Variance Explained		54.53	47.86

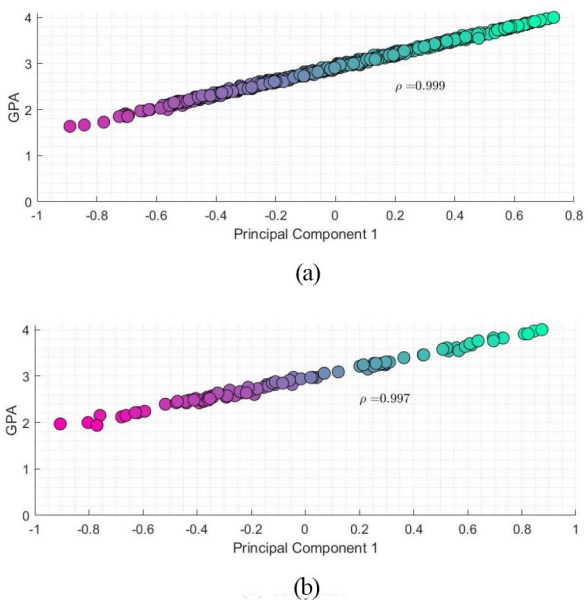


Fig. 4. Linear relationship between the most significant PC and the cumulative GPA. (a) Pre-KI years. (b) KI years.

GPA. The difference in variance explained by the first PCs for the pre-KI and KI years is 7%, thus the GPA explains 7% less of the total variation in the performance of individual courses for the KI students.

An analysis of the data from only the third year has been previously presented in [8] for the pre-KI students. That analysis has been reprised in this article to also include the KI students, noting that the results are consistent but very slightly different, as the set of pre-KI students that participate in this article is a subset of the set of students from the previous study. The previous study only required that students had a complete set of third-year grades in ECE, while this article required a complete set of first-, second-, and third-year grades in ECE.

When compared to the PCA results for first-, second-, and third-year data, a similar trend can be seen in the PCA results for the third year only data. The first PCs and the percentage of total variance explained can be seen in Table III. The study has identified a 5% reduction in the variance of the core ECE technical courses explained by the dominant PC,

TABLE III
FIRST PCS AND THEIR PERCENT OF TOTAL VARIANCE EXPLAINED FOR ONLY THIRD-YEAR DATA

	$PC1_{pre\text{-}KI}$	$PC1_{KI}$
ECE311	0.41	0.41
ECE312	0.41	0.47
ECE331	0.40	0.35
ECE332	0.39	0.34
ECE341	0.41	0.46
ECE342	0.40	0.35
% of Total Variance Explained	59.01	53.76

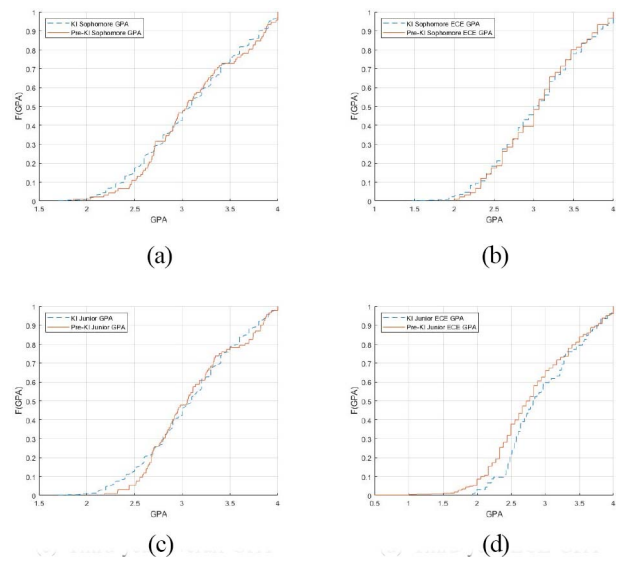


Fig. 5. ECDFs for both cumulative GPA and ECE GPA over the pre-KI and KI years. (a) Second-year overall GPA. (b) Second-year ECE GPA. (c) Third-year overall GPA. (d) Third-year ECE GPA.

which is still almost perfectly correlated with the cumulative GPA. Another way to say this is that the overall performance, measured through the cumulative GPA, contributes 5% less to individual course performance, measured through course grades, for KI years when compared to the pre-KI years.

D. Kolmogorov–Smirnov Test

The difference in distributions was examined for two different sets of grades at the end of the second year as well as the end of the third year. The first set of grades is the cumulative GPA of the students while the second set of grades is the GPA composed of just ECE courses. The empirical cumulative distribution functions (ECDFs) for these different sets of grades are presented in Fig. 5. In particular, the GPAs shown in Fig. 5(b) are calculated from the first- and second-year ECE courses and represent the performance within the ECE major prior to entering the third year, while the GPAs shown in Fig. 5(d) are calculated from the third-year ECE courses and represent the performance within the ECE major during the third year.

The purpose of running the two-sample KS test on the second-year GPA sets is to show that the students from the pre-KI and KI years are drawn from the same population, effectively showing that both groups are starting from the

same performance base upon entering the third year. Similarly, the purpose of running the two-sample KS test on the third-year cumulative GPA is to show that the KI students are still part of the same overall population as the pre-KI students at the end of the third year. In the prior three cases, the KS test concluded that there is no difference in the distributions with $D_{\mathrm{KS}} = 0.0944$ for the third-year cumulative GPA, $D_{\mathrm{KS}} = 0.0813$ for the second-year cumulative GPA, and $D_{\mathrm{KS}} = 0.0603$ for the second-year ECE GPA. For the final case of running the two-sample KS test on the third ECE GPA, the distributions were determined to be statistically different with $D_{\mathrm{KS}} = 0.1844$. It is noted that the distribution of the third-year ECE grades has shifted to the right, indicating a rise in the performance of each student in the third year after the implementation of the KI activities. As seen in Fig. 5(d), the KS distance is greatest when the ECE GPA is 2.4. Thus, all students benefited from the KI activities with the greatest benefit for those with lower GPAs.

E. Analysis on Subsets of Pre-KI Students

To investigate the possible effects of such a disparity between sample sizes of pre-KI and post-KI student sets, the nonparametric analysis was performed on subsets of the pre-KI students. The entire set of pre-KI students, gathered over 27 years, was separated into five subsets spanning approximately five years each. Each of the subsets contained approximately 120 pre-KI students. All three parametric analysis techniques were performed on the subsets, to compare each subset of pre-KI students to post-KI students. The results of each subset analysis echo the results from the analysis on the entire set of pre-KI students, with very minor fluctuations in the correlation coefficients, PCs, and location (GPA value) where the KS test indicates a significant difference between ECDFs.

VI. Conclusion

In this article, an analysis of the correlations between two semesters of topical ECE courses as well as the correlations between mathematics and ECE courses for the pre-KI and KI years is presented. Also presented is an analysis of the dominating PC generated from the ECE grade data, and an analysis of the two-sample KS test on the second- and third-year grade distributions for the pre-KI and KI years. The technical results of the correlation analysis and PCA explain two main points. The first is that there is a moderately strong correlation between the performance in prerequisite and requisite courses for both groups of students, while the intertopical correlations are greater for KI students. The second is that the cumulative GPA is less of a performance indicator for individual ECE courses for the KI students. This implies that students are, to a greater degree, seeing the bigger picture within the ECE curriculum, and that the GPA is becoming less of an indicator of performance due to the changes made by CSU's RED implementation. The technical results from the two-sample KS test show that there is a statistically significant positive change in ECE GPA distribution after the implementation of the LSMs and KI activities. Altogether, this article shows that there has been a positive, quantifiable change to the performance of undergraduate ECE students at CSU as a result of the RED grant, and that the practices put in place are set to act as a model for other colleges and universities in the future.

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