An Assessment of Average Course Grades in a Converged Classroom Environment

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Successful decision-making for a classroom modality requires knowledge of how students learn, the use of technology in classrooms, and student perception and satisfaction with various content delivery methods. The problem is that growth and diffusion of technology have outpaced knowledge of the utility of investment in a converged multimedia classroom modality. The purpose of this study was to conduct an empirical analysis of the relationship of student satisfaction with a converged classroom that provides factors of (a) real-time access to an instructor, (b) multimedia format types, and (c) flexible enrollment options for online, local, or a combined presence.

INTRODUCTION

The converged classroom simultaneously combines both hybrid (i.e., on-campus) and online learning environments. Unlike traditional courses that meet face-to-face twice per week, hybrid sections of the course meet one day per week on campus and have pre-recorded course materials including narrated Powerpoint slides, assignments, and exams which are delivered via the Brightspace Desire2Learn™ (D2L) online learning environment. Online sections of the course meet one day per week using the Blackboard Collaborate learning environment, which is part of Brightspace D2L, and also includes the same narrated Powerpoint slides, assignments, and exams as for the hybrid students.

All converged courses are developed to include a 50% pre-recorded lecture video (i.e., the narrated Powerpoint slides) and a 50% Live Session component. The Live Sessions are 'converged,' meaning both the hybrid and online sections can view the lecture live. The Live Sessions are recorded and archived for students who are unable to attend the Live lecture on the scheduled day and time. The archived recordings are intended for online students only and can be accessed 24/7. They are archived in chronological order and can be accessed in Blackboard Collaborate™ 24/7 simply by clicking on the desired Live Session date.

The professor is not shown in the archived recording; however, all materials shown on the computer screen on the instructor's console as well as the professor's voice is captured in the recordings. Therefore, if a professor spends time working through a mathematical problem during the Live Session, for example, students who view the archived recording can see and listen to how the instructor works through the problem step-by-step as the instructor writes on the computer screen by activating a pen with a choice of four different ink colors – black, red, blue, and green. Highlighting capabilities in different colors are also available.

This study analyzes the average course grades in seven different Industrial Engineering Technology (IET) courses during the 2015-16 academic year utilizing the same converged classroom technology and taught by the same professor. Several research questions (RQ) are explored as follows:

RQ1: Is there a significant difference in average course grade between on-campus students and distance students? The null hypothesis postulates no relationship exists between hybrid student and online students.

RQ2: Is there a significant difference in average course grade among age groups? The null hypothesis postulates no difference among age groups.

RQ3: Is there a significant difference in average course grade between genders? The null hypothesis postulated no difference between genders.

RQ4: Is there a significant difference in average course grade between IET majors and other majors? The null hypothesis postulates no difference between the two group majors.

RQ5: Is there a significant difference in average course grade between Fall and Spring semester? The null hypothesis postulates no difference between the two semesters.

RQ6: Is there a significant difference in average course grade among class standing (Freshmen, Sophomore, Junior, or Senior)? The null hypothesis postulates no difference among class standing.

RQ7: Is there a significant relationship between average course grade and cumulative grade point average?

The primary objective of this research is to determine which main effect predictor variable(s), if any, have a significant effect on predicting average course grades. This will be addressed by forming a reduced regression model that is originally based on a full 7-factor multivariate regression model.

LITERATURE REVIEW

Hybrid courses combine instructional elements from traditional face-to-face (F2F) and online course formats (El Mansour & Mupinga, 2007). Hybrid courses, in many circles, is synonymous with a converged classroom and, therefore, the two terms may be used interchangeably. This type of learning environment differs from a traditional classroom teaching environment in two distinct ways: 1) students are first introduced to the substantive material and are required to read and understand the material before coming to class for the Live Session; and 2) during the Live Session, the instructor helps to clarify points of confusion or difficulty, work through problems, etc. (Haughton and Kelly, 2015). Because of changing student demographics and efforts to make courses more accessible to students, converged (or hybrid) course offerings have increased rapidly (Blier, 2008). For example, converged courses not only decrease travel time for student who live in rural areas (Yudko, Hirokawa, and Chi, 2008), they also decrease travel time for students who live in metropolitan areas where traffic is heavily congested. The converged classroom also accommodates students' busy schedules away from school; principally, work and family obligations (Aslanian, 2001). Research also cites convenience, flexibility, currency of material, rapid feedback, and customized learning as key factors for online students (Harasim, 1990; Hackbarth, 1996; Kiser, 1999, Matthews, 1999; Swan et al., 2000; Wiles & Keyser, 2016). Therefore, it is likely that hybrid courses will continue to grow and stem the rising costs of higher education (Woodworth & Applin, 2007; Allen and Seaman, 2010).

Whereas Kolb's learning theory of pedagogical learning for instructional design (Kolb, 1984) combined with Knowles' learning theory of adult learning (Knowles, 1990, 1980) were instrumental in assessing the learning needs of both on-campus and online engineering students, the effectiveness of student attitudes, student satisfaction, and performance varies across the literature.

Lam (2009) analyzed the performance of traditional vs. online formats of an undergraduate computer programming course using regression analysis, concluding that delivery mode did not influence average course grades in a statistically significant sense; however, students' cumulative grade point average (GPA) was the only significant predictor. In analyzing the success rates of F2F vs. online students in two different business courses, Wilson & Allen (2011) also concluded that cumulative GPA was the most significant predictor of course grade, regardless of delivery mode. Xu and Jaggars (2014) conclude, in a study of over 51,000 students initially enrolled in one of Washington State's 34 community or technical colleges during Fall 2014, that the online format had a significantly negative relationship with standardized course grade, indicating that the typical student had more difficulty succeeding in online course vs. traditional F2F courses. Driscoll, et al., (2011) concluded no significant difference in student performance and student satisfaction between traditional vs. online sections of an introductory sociology course taught by the same professor over multiple semesters with little change in course materials or assessment instruments. Reisetter et al. (2007) found no significant differences between traditional and online students in their course satisfaction and learning.

To stimulate both student performance and student satisfaction, Sauers and Walker (2004) state that there is a need to identify the best use of online instruction and how to implement the tools of online learning management systems. Further, undergraduate students suggested more instructor/student training in the use of technology as well as the recording of synchronous sessions for later review (Bonakdarian, Wittaker, & Bell, 2009); Wood, 2010). Effective instructors must play a far more prominent and interactive role by being a present and active participant if they hope to foster effective student thinking (Tassel & Schmitz (2014); Schubert-Irastorza & Fabry (2011).

METHODOLOGY

The research design consists of obtaining students' average course grades for seven different Industrial Engineering Technology (IET) converged courses taught in the Fall and Spring semesters of the 2015-16 academic year at a four-year comprehensive university. Students outside of the IET major were permitted to register for an IET course if it was cross-referenced to fit their particular major requirements. For example, business majors were permitted to register for IET 2227 – Introduction to Statistics to satisfy their Statistics requirement. As another example, IET 4151 – Operations Management is cross-listed with SYE 3700 – Production and Inventory Control, although both courses are the same – IET 4151 is for Industrial Engineering Technology majors and SYE 3700 is for Systems Engineering majors.

All seven courses in this study are converged classroom-type courses, meaning each course consists of a hybrid (i.e., on-campus) section as well as an online section. Both sections simultaneously attend the Live Session. The Blackboard CollaborateTM technology permits active participation for online students to speak (via a headset microphone) or text responses so that everyone in the class can hear or read the dialogue exchange with the professor. A primary benefit for online students is that, although not physically present in the classroom, the online student is still an active participant who can see and hear everything during the Live Session from the convenience of home or work.

All seven courses were taught by the same professor utilizing the same classroom technology, specifically, Desire2LearnTM and Blackboard CollaborateTM.

Each course includes 16 Learning Modules (one Learning Module each for 16 weeks). Included with each Learning Module is an Overview Page, the pre-recorded lecture videos, posted Powerpoint slides, homework assignments, and any ancillary materials accessed by links such as handouts, tables, videos, Excel problems, etc. Students are required to submit their homework assignments via a Dropbox folder designated for that particular assignment. Quizzes and exams vary from 1) downloading these assessments, completing them, saving the file, and then downloading the submission in the appropriate Dropbox folder or 2) writing an online quiz or exam by clicking on the Quizzes tab in the D2L navbar and then clicking on the appropriate assessment (quiz or exam), opening the file, and then completing the exam. Online exams are submitted automatically when the student selects 'Submit' when closing out the session. The professor offers alternate types of assessments each semester to counter the possibility of students using recycled quizzes or exams from prior semester.

Students are expected to view the pre-recorded lecture videos, read the textbook, review the posted Powerpoint slides, and work problems on their own prior to the Live Session. During the Live Session, with the expectation of familiarity of concepts for the week from the professor's perspective, the professor uses the Live Session to work through problems in the chapter and answer any questions that students may have.

This type of classroom learning differs from traditional classroom learning in that, with traditional classroom learning, the professor meets with students face-to-face on typically a M-W or T-R schedule, whereby the professor will discuss concepts and work examples through each chapter. With converged classroom learning, the expectation that students will view the pre-recorded lecture, read the textbook, review the posted Powerpoint slides, and work problems on their own takes the place of one day in traditional classroom learning environment prior to the Live Session. The Live Session serves as the second day of traditional classroom learning. The anticipated trade-off is that time is more efficiently utilized by the professor if students are already familiar with the chapter concepts prior to attending the Live Session. The Live Session is thus utilized for solving problems and answering questions. Hence, the same instruction and learning occurs as in a traditional classroom environment, albeit in a different format with converged classrooms.

Once all assessments have been graded with appropriate weights assigned as outlined in the Syllabus, the final average course grade for each student is determined and a letter grade is posted in the Grades tab for each student for completing the course.

In this study, the full model is based on a 7-factor, multi-variate regression model that includes the response variable and seven main effect predictor variables along with all higher-order interaction terms. Hence, the analysis consists of 127 different combinations of variables as shown below.

$$\text{1-factor model} = \binom{7}{1} = 7 \text{ main effects}$$

$$\text{2-factor interactions} = \binom{7}{2} = 21 \text{ two-factor interactions}$$

$$\text{3-factor interactions} = \binom{7}{3} = 35 \text{ three-factor interactions}$$

$$\text{4-factor interactions} = \binom{7}{4} = 35 \text{ four-factor interactions}$$

$$\text{5-factor interactions} = \binom{7}{5} = 21 \text{ five-factor interactions}$$

$$\text{6-factor interactions} = \binom{7}{6} = 7 \text{ six-factor interactions}$$

$$\text{7-factor interactions} = \binom{7}{7} = 1 \text{ seven-factor interaction}$$

Coded details of the main effect variables in the model are shown below:

Response variable:

$\hat{y}$ = course average

Predictor variables:

X1 = Gender (1 = Female; 2 = Male)
X2 = Age Group (1 = 20-29; 2 = 30-39; 3 = 40-49; 4 = 50-59)
X3 = Term (1 = Fall 2015; 2 = Spring 2016)
X4 = Registration (1 = On-campus student; 2 = Distance student)
X5 = Major (1 = IET; 2 = Other)
X6 = Class Standing (1 = Freshman; 2 = Sophomore; 3 = Junior; 4 = Senior)
X7 = Cumulative grade point average

Following an examination of the full model, the researchers address the research questions provided in the Introduction section.

Reaching the final reduced model employs a four-step process. (1) Once the full multivariate model is analyzed and *p*-values for all variables are compared to the researchers' desired significance level, significant terms, as well as some non-significant terms (to aid higher-order terms requiring non-significant lower-order main effect terms), will be retained to form a (2) reduced model with main effects and higher-order terms. The reduced model with higher-order terms then leads to a (3) reduced model with main effects only terms. (4) The final reduced model consists of two main effects only. A series of diagnostics, including an analysis of residuals, will then be performed on the reduced model to test its validity in predicting average course grades. The researchers use the significance level criterion of $\alpha = 0.05$ to determine whether variables are statistically significant.

RESEARCH FINDINGS

The participants in this study include students at a four-year comprehensive university who took converged Industrial Engineering Technology (IET) courses (i.e., including on-campus (hybrid) and distance students during the Live lecture session) with the same professor using the same online classroom delivery technology (Blackboard Collaborate™ online classroom technology in the Desire2Learn™ (D2L) online learning environment during the Fall 2015/Spring 2016 academic year. Results for the full model are shown below.

(1) Full Multivariate Model with Main Effects and Higher-Order Terms:

Estimated Effects and Coefficients for Course Avg. (Y) (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		157.6	28.088	5.61	0.000
Gender (X1)	-25.0	-12.5	21.056	-0.59	0.554**
Age Group (X2)	193.2	96.6	42.065	2.30	0.023*
Term (X3)	48.7	24.4	21.295	1.14	0.255**
Registration (X4)	-100.8	-50.4	35.070	-1.44	0.153**
Major (X5)	-42.5	-21.2	16.719	-1.27	0.206**
Standing (X6)	-146.8	-73.4	35.005	-2.10	0.038*
Cum.GPA (X7)	-85.3	-42.6	43.330	-0.98	0.327**
Gender (X1)*Age Group (X2)	-24.6	-12.3	15.342	-0.80	0.424
Gender (X1)*Term (X3)	-58.3	-29.2	22.613	-1.29	0.199
Gender (X1)*Registration (X4)	-17.6	-8.8	10.113	-0.87	0.386
Gender (X1)*Major (X5)	-9.8	-4.9	7.759	-0.63	0.530
Gender (X1)*Standing (X6)	-8.5	-4.2	14.470	-0.29	0.769
Gender (X1)*Cum.GPA (X7)	-54.7	-27.3	29.267	-0.93	0.352
Age Group (X2)*Term (X3)	60.2	30.1	22.933	1.31	0.192
Age Group (X2)*Registration (X4)	-40.9	-20.4	24.496	-0.83	0.406
Age Group (X2)*Major (X5)	-54.7	-27.4	12.691	-2.16	0.033*
Age Group (X2)*Standing (X6)	-222.2	-111.1	50.738	-2.19	0.030*
Age Group (X2)*Cum.GPA (X7)	-268.9	-134.4	89.128	-1.51	0.134
Term (X3)*Registration (X4)	-4.5	-2.3	8.833	-0.26	0.797

Term (X3)*Major (X5)	10.7	5.3	4.727	1.13	0.260
Term (X3)*Standing (X6)	5.4	2.7	11.421	0.24	0.814
Term (X3)*Cum.GPA (X7)	16.6	8.3	10.131	0.82	0.414
Registration (X4)*Major (X5)	40.3	20.2	13.907	1.45	0.150
Registration (X4)*Standing (X6)	158.7	79.4	42.339	1.87	0.063
Registration (X4)*Cum.GPA (X7)	198.0	99.0	59.217	1.67	0.097
Major (X5)*Standing (X6)	21.0	10.5	5.143	2.04	0.043*
Major (X5)*Cum.GPA (X7)	-4.8	-2.4	11.286	-0.21	0.830
Standing (X6)*Cum.GPA (X7)	175.6	87.8	35.736	2.46	0.015*
Gender (X1)*Age Group (X2)*Term (X3)	-54.3	-27.2	22.974	-1.18	0.239
Gender (X1)*Age Group (X2)* Registration (X4)	-20.7	-10.4	9.965	-1.04	0.300
Gender (X1)*Term (X3)* Registration (X4)	2.3	1.2	1.238	0.94	0.348
Gender (X1)*Age Group (X2)* Major (X5)	-4.7	-2.3	8.178	-0.29	0.775
Gender (X1)*Term (X3)*Standing (X6)	2.4	1.2	12.289	0.10	0.922
Gender (X1)*Age Group (X2)* Cum.GPA (X7)	-82.2	-41.1	21.223	-1.94	0.055
Gender (X1)*Term (X3)*Cum.GPA (X7)	-9.1	-4.5	2.755	-1.65	0.101
Gender (X1)*Registration (X4)* Cum.GPA (X7)	5.5	2.7	2.755	0.99	0.323
Gender (X1)*Major (X5)*Cum.GPA (X7)	-1.9	-0.9	5.299	-0.18	0.859
Gender (X1)*Standing (X6)* Cum.GPA (X7)	-15.6	-7.8	20.884	-0.37	0.710
Age Group (X2)*Term (X3)* Registration (X4)	1.6	0.8	8.223	0.10	0.921
Age Group (X2)*Term (X3)*Major (X5)	3.6	1.8	4.501	0.40	0.692
Age Group (X2)*Registration (X4)* Major (X5)	36.0	18.0	13.493	1.33	0.185
Age Group (X2)*Term (X3)* Standing (X6)	-12.0	-6.0	19.505	-0.31	0.759
Age Group (X2)*Registration (X4)* Standing (X6)	91.9	45.9	30.055	1.53	0.129
Age Group (X2)*Major (X5)* Standing (X6)	19.1	9.6	11.509	0.83	0.407
Age Group (X2)*Term (X3)* Cum.GPA (X7)	10.9	5.5	9.375	0.58	0.561
Age Group (X2)*Registration (X4)* Cum.GPA (X7)	9.9	5.0	9.375	0.53	0.598
Age Group (X2)*Major (X5)* Cum.GPA (X7)	11.2	5.6	14.929	0.38	0.707
Age Group (X2)*Standing (X6)* Cum.GPA (X7)	372.9	186.5	84.927	2.20	0.030*
Term (X3)*Registration (X4)* Major (X5)	-1.8	-0.9	3.047	-0.30	0.768
Term (X3)*Registration (X4)* Cum.GPA (X7)	14.9	7.5	9.481	0.79	0.432
Term (X3)*Major (X5)*Cum.GPA (X7)	-8.2	-4.1	4.508	-0.91	0.365
Registration (X4)*Major (X5)* Cum.GPA (X7)	1.7	0.8	6.505	0.13	0.898
Registration (X4)*Standing (X6)* Cum.GPA (X7)	-201.8	-100.9	58.058	-1.74	0.085
Gender (X1)*Term (X3)* Registration (X4)*Cum.GPA (X7)	-15.4	-7.7	2.755	-2.79	0.006*
Age Group (X2)*Term (X3)* Registration (X4)*Cum.GPA (X7)	-3.4	-1.7	9.375	-0.18	0.857

```
S = 7.62659     PRESS = *
R-Sq = 44.97%   R-Sq(pred) = *%   R-Sq(adj) = 22.38%
```

The full model contains significant terms whose p-values ≤ 0.05 (p-values with one asterisk) and non-significant main effect terms whose p-values > 0.05 (p-values with two asterisks) that must be retained because some significant higher-order terms require these main effects in the full model.

The regression equation for the Full Model is:

$\hat{y}$ = 157.6 – 12.5 Gender (X1) + 96.6 Age Group (X2) + 24.4 Term (X3) – 50.4 Registration (X4) – 21.2 Major (X5) – 73.4 Standing (X6) – 42.6 Cum. GPA (X7) – 27.4 Age Group (X2) * Major (X5) – 111.1 Age Group (X2) * Standing (X6) + 10.5 Major (X5) * Standing (X6) + 87.8 Standing (X6) * Cum. GPA (X7) + 186.5 Age Group (X2) * Standing (X6) * Cum. GPA (X7) – 7.7 Gender (X1) * Term (X3) * Registration (X4) * Cum. GPA (X7)

A quick general overview of these results reveal some important conclusions: 1) R^2 = 44.97%, indicating a moderate amount of variation in the full model is explained by the variables in the full model; 2) R^2-adjusted decreases to 22.38%, meaning the variation in predicting average course grades decreases with the addition of new variables that do not produce a large enough reduction in the residual sum of squares to compensate for the loss of one residual degree of freedom associated with each new variable; 3) The full multivariate model tests H_o: $\beta_1 = \beta_2 = \cdots \beta_n = 0$ vs. H_a: at least one $\beta_j \neq 0$. We find that at least one variable is significant (p-value = 0.000) at the $\alpha = 0.05$ level of significance; 3) Only two main effect variables, Age Group (X2) and Class Standing (X6) appear to be significant at $\alpha = 0.05$, *as they relate to other variables* in the full model. Gender (X1), Term (X3), Registration (X4), and Cum. GPA (X7) are retained in the full model solely due to significant higher-order terms that require these main effect variables.

(2) Reduced Model with Main Effects and Higher-Order Terms:

Assumptions in the reduced model include: 1) errors are uncorrelated random variables with mean zero; 2) errors have constant variance; and 3) errors are normally distributed.

Results for the reduced model with higher-order terms are as follows:

```
The regression equation for the reduced model is:
Course Avg. (Y) = 24.89 - 2.26 Gender (X1) + 6.991 Age Group (X2) + 0.215 Term (X3)
                  + 1.144 Registration (X4) + 13.29 Major (X5) + 14.11 Standing (X6)
                  + 7.50 Cum.GPA (X7) + 1.128 Gender(X2) * Major(X5) - 3.407 Age
                  Group(X2) * Standing(X6) - 3.587 Major(X5) * Standing(X6) - 0.641
                  Standing(X6) * Cum.GPA(X7) + 0.3513 Age Group(X2) * Standing(X6)*
                  Cum.GPA(X7) - 0.0458 Gender(X1) * Term(X3) * Registration(X4) *
                  Cum.GPA(X7)
```

Predictor	Coef	SE Coef	T	P
Constant	24.89	64.13	0.39	0.698
Gender (X1)	-2.260	2.130	-1.06	0.290
Age Group (X2)	6.991	7.977	0.88	0.382
Term (X3)	0.215	2.491	0.09	0.931
Registration (X4)	1.144	2.767	0.41	0.680
Major (X5)	13.29	16.16	0.82	0.412
Standing (X6)	14.11	16.04	0.88	0.380
Cum.GPA (X7)	7.50	16.64	0.45	0.653
(X2)*(X5)	1.128	1.991	0.57	0.572
(X2)*(X6)	-3.407	2.599	-1.31	0.192
(X5)*(X6)	-3.587	3.995	-0.90	0.370
(X6)*(X7)	-0.641	4.262	-0.15	0.881
(X2)*(X6)*(X7)	0.3513	0.4777	0.74	0.463
(X1)*(X3)*(X4)*(X7)	-0.0458	0.2655	-0.17	0.863

```
S = 8.01214   R-Sq = 20.2%   R-Sq(adj) = 14.3%

Analysis of Variance

Source           DF        SS      MS     F      P
Regression       13   2864.48  220.34  3.43  0.000
Residual Error  176  11298.21   64.19
Total           189  14162.69
```

At the $\alpha = 0.05$ level of significance, the reduced model is significant (*p*-value = 0.000) although none of the terms in the reduced model are significant (*p*-values for all terms > 0.05). The standard deviation is s = 8.01214 and R^2 = 20.2%. Since none of the terms in the reduced model with higher-order terms are statistically significant, this model is of little value.

If the non-significant higher-order interaction terms are removed and the reduced model is re-run, this results in a more useful reduced model with only main effects. The results are as follows:

(3) Reduced Model with Main Effects Only:

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The regression equation is
Course Avg. (Y) = 60.103 - 2.385 Gender (X1) + 0.1282 Age Group (X2)
                  - 0.178 Term (X3) + 0.821 Registration (X4) + 1.044 Major (X5)
                  + 3.355 Standing (X6) + 6.477 Cum.GPA (X7)


Predictor             Coef  SE Coef      T      P
Constant            60.103    9.075   6.62  0.000
Gender (X1)         -2.385    1.404  -1.70  0.091
Age Group (X2)      0.1282   0.9594   0.13  0.894
Term (X3)           -0.178    1.233  -0.14  0.885
Registration (X4)    0.821    1.287   0.64  0.524
Major (X5)           1.044    1.838   0.57  0.571
Standing (X6)        3.355    1.681   2.00  0.047*
Cum.GPA (X7)         6.477    1.185   5.46  0.000*


S = 7.96350   R-Sq = 18.5%   R-Sq(adj) = 15.4%


Analysis of Variance

Source           DF        SS      MS     F      P
Regression        7   2620.73  374.39  5.90  0.000
Residual Error  182  11541.95   63.42
Total           189  14162.69
```

Although both reduced models are statistically significant (*p*-values = 0.000), the reduced model with main effects only proves more useful than the reduced model with higher-order terms because we now observe two main effects that are statistically significant: Standing (X6) and Cum. GPA (X7). Next, a final reduced model is run that includes only the two significant main effects. The results are as follows:

(4) Final Reduced Model with Significant Main Effects Only: Standing (X6) and Cum. GPA (X7)

Regression Analysis: Course Avg. (Y) versus Standing (X6), Cum.GPA (X7)

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The regression equation is
Course Avg. (Y) = 58.051 + 3.276 Standing (X6) + 6.611 Cum.GPA (X7)
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```
Predictor          Coef  SE Coef     T      P
Constant         58.051    7.272  7.98  0.000
Standing (X6)     3.276    1.588  2.06  0.041*
Cum.GPA (X7)      6.611    1.122  5.89  0.000*


S = 7.93084   R-Sq = 17.0%   R-Sq(adj) = 16.1%


Analysis of Variance

Source            DF       SS      MS      F      P
Regression         2   2400.7  1200.4  19.08  0.000
Residual Error   187  11762.0    62.9
Total            189  14162.7

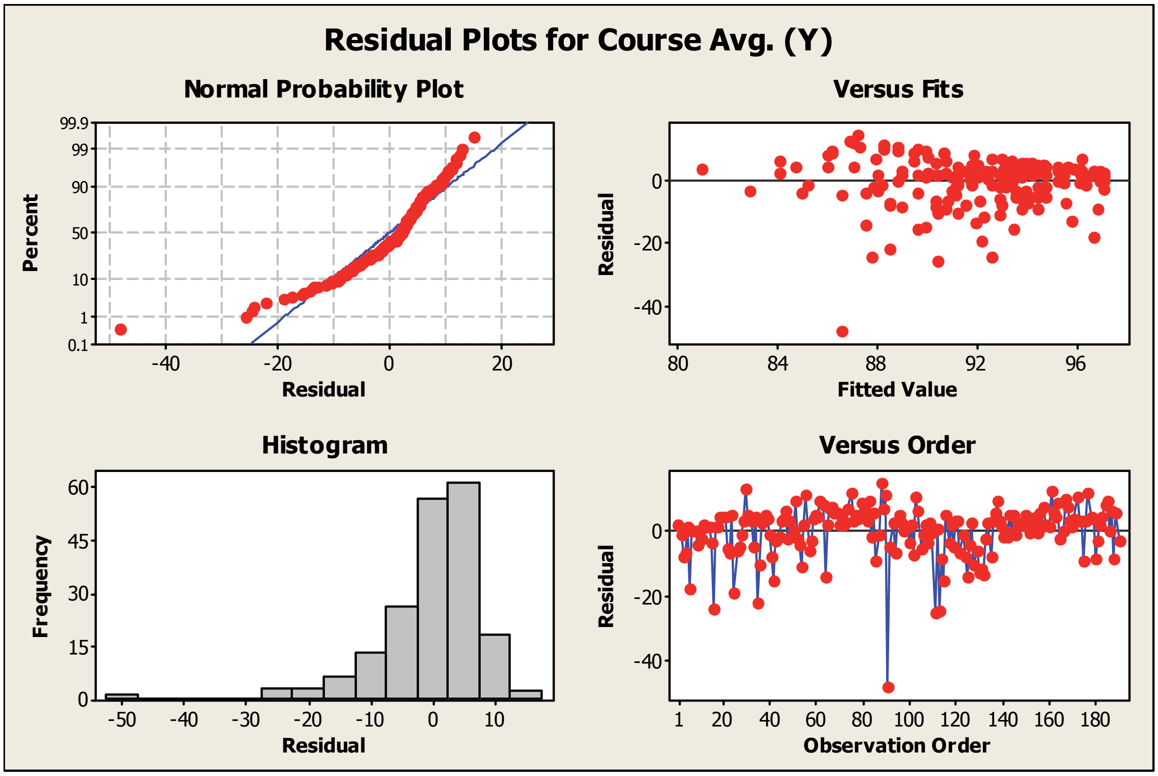

Source          DF  Seq SS
Standing (X6)    1   216.6
Cum.GPA (X7)     1  2184.1
```

The final reduced model becomes:
Course Avg. (Y) = 58.051 + 3.276 Standing (X6) + 6.611 Cum.GPA (X7).

Next, diagnostic procedures were applied, including residuals analysis, to determine the final reduced model's validity in predicting average course grades. We begin with a Four-in-One plot of the residuals for Average Course Grade and Cumulative GPA, which includes a Normal Probability Plot; a Histogram of Residuals; Residuals plotted against Fitted Values; and Residuals plotted in Observation Order.

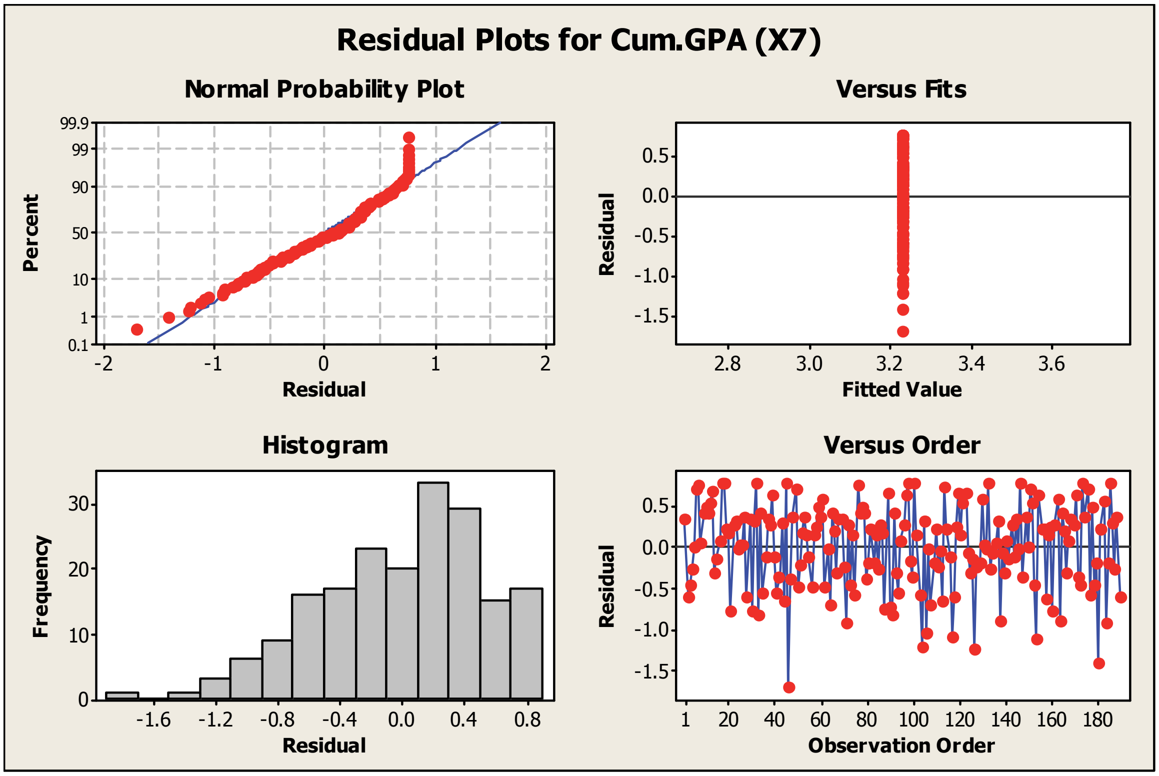
The Four-in-One plot for the response variable, Average Course Grade, is shown in Figure 1. The Normal Probability Plot of residuals for Average Course Grade reveals non-normality, as indicated by the tails at both extremes of the plot, although there is some semblance of normality in the middle portion of the plot. The Histogram of residuals corroborates what we see in the Normal Probability Plot; that is, some semblance of normality is indicated in this left-skewed distribution; however, the Histogram essentially indicates non-normality in the distribution of data. The residuals vs. fitted values appear to converge towards the higher grades; thus, the presence of a positive relationship, or non-constant variance, is observed. The residuals plotted in observation order reveals some variability in the data. Fluctuations in observation order display randomness in much of the observations with some periods of possible multicollinearity both above and below zero.

FIGURE 1
A FOUR-IN-ONE DIAGRAM OF RESIDUALS FOR AVERAGE COURSE GRADE



The Four-in-One plot for the predictor variable, Cumulative GPA, is shown in Figure 2. The Normal Probability Plot of residuals for Cumulative GPA reveals non-normality at the extremities of the plot; however, the majority of the plot reveals normality. A possible outlier is also noted in the plot. The Histogram of residuals corroborates what we see in the Normal Probability Plot; that is, some semblance of normality is indicated in this left-skewed distribution; however, the Histogram indicates a non-normal bell-shaped distribution, or non-normality. The residuals vs. fitted values indicate a definite linear relationship, therefore, evidence of constant variance between residuals and fitted values is observed. The residuals plotted in observation order reveals both a great deal of variability and randomness in the data. The fluctuations indicate graphically that no multicollinearity exists among the residuals for Cumulative GPA.

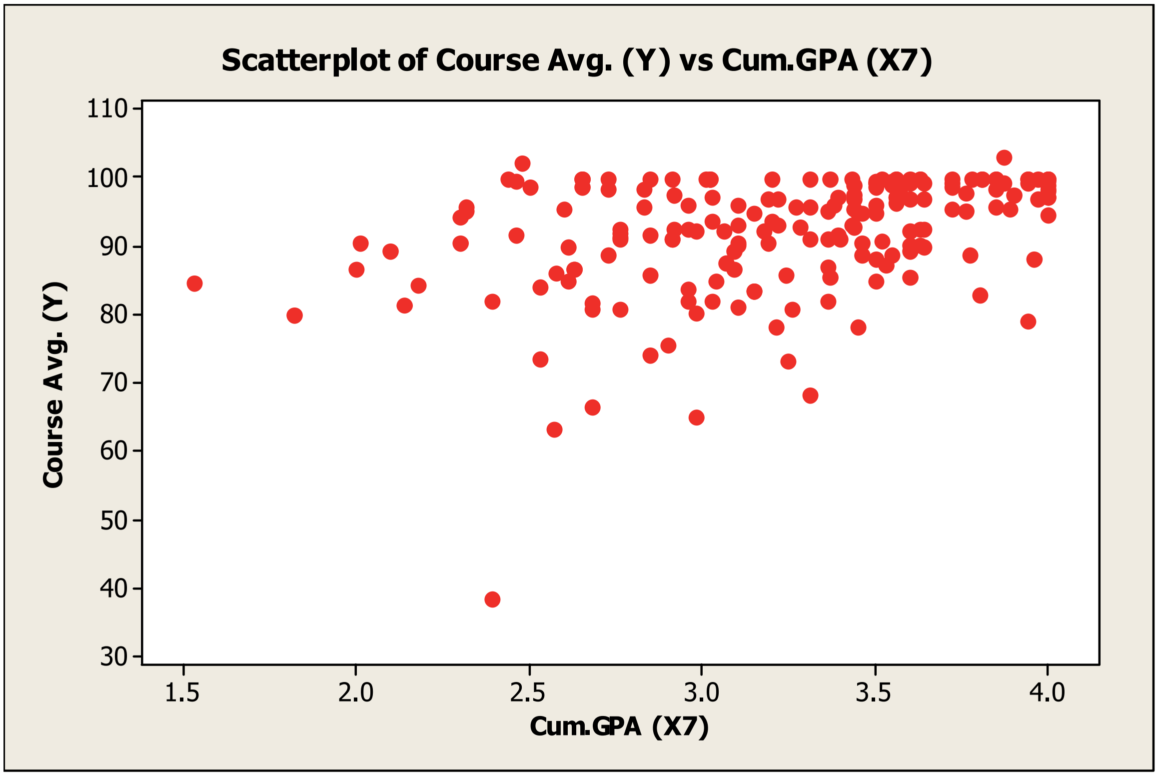
FIGURE 2
A FOUR-IN-ONE DIAGRAM OF RESIDUALS FOR CUMULATIVE GPA



A Scatterplot of Average Course Grades vs. Cumulative GPA is shown in Figure 3. A positive relationship is observed; that is, Average Course Grades appear to increase as Cumulative GPA increases.

Analysis of the (4) Final Reduced Model ANOVA table shows both the Final Reduced Model *p*-value, the Standing *p*-value, and Cumulative GPA *p*-value $< \alpha = 0.05$, leading to the conclusion that the final reduced model and the two predictor variables are statistically significant. Further, the standard deviation is $s = 7.99921$ and $R^2 = 15.1\%$, meaning that 15.1% of the variability in the response variable, $\hat{y}$, is explained by the predictor variables, Class Standing and Cumulative GPA. The Pearson correlation coefficient is $r = 38.9\%$, indicating a moderate, positive linear relationship between Average Course Grade and the two predictor variables, as we saw in both normal probability plots.

FIGURE 3
SCATTERPLOT OF AVERAGE COURSE GRADES VS. CUMULATIVE GPA



5. CONCLUSIONS

Next, we shall address each of the research questions.

RQ1: Is there a significant difference in average course grade between on-campus students and distance students? The null hypothesis postulates no relationship exists between hybrid student and online students.

H_o: There is no difference in average course grades between on-campus students and distance students
H_a: There is a difference in average course grades between on-campus student and distance students

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 91.9 + 0.13 Registration (X4)


Predictor              Coef  SE Coef      T      P
Constant             91.910    1.912  48.07  0.000
Registration (X4)     0.133    1.280   0.10  0.917


S = 8.67924   R-Sq = 0.0%   R-Sq(adj) = 0.0%
```

```
Analysis of Variance

Source           DF        SS     MS     F      P
Regression        1      0.81   0.81  0.01  0.917
Residual Error  188  14161.88  75.33
Total           189  14162.69
```

It is observed that the Registration p-value of 0.917 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Registration (i.e., on-campus students vs. distance students) is not a significant variable in the full model. Further, the standard deviation, s, is quite large at s = 8.67924 and both R^2 and R^2-adjusted = 0.0%, indicating the variable Registration explains no variation in predicting average course grades.

RQ2: Is there a significant difference in average course grade among age groups? The null hypothesis postulates no difference among age groups.

H_o: There is no difference in average course grades among age groups
H_a: There is a difference in average course grades among age groups

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 90.7 + 0.998 Age Group (X2)


Predictor          Coef  SE Coef      T      P
Constant         90.726    1.386  65.45  0.000
Age Group (X2)   0.9980   0.8997   1.11  0.269


S = 8.65122   R-Sq = 0.7%   R-Sq(adj) = 0.1%


Analysis of Variance

Source           DF        SS     MS     F      P
Regression        1     92.11  92.11  1.23  0.269
Residual Error  188  14070.58  74.84
Total           189  14162.69
```

It is observed that the Age Group p-value of 0.269 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Age Group (i.e., 20-29, 30-39, 40-49, 50-59) is not a significant variable in the full model. Further, the standard deviation is s = 8.65122 with R^2 = 0.7% and R^2-adjusted = 0.1%, indicating the variable Age Group explains virtually no variation in predicting average course grades.

RQ3: Is there a significant difference in average course grade among genders? The null hypothesis postulated no difference among genders.

H_o: There is no difference in average course grades between genders
H_a: There is a difference in average course grades between genders

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 96.7 - 2.61 Gender (X1)
```

```
Predictor      Coef  SE Coef      T      P
Constant     96.658    2.587  37.37  0.000
Gender (X1)  -2.610    1.437  -1.82  0.071


S = 8.60428   R-Sq = 1.7%   R-Sq(adj) = 1.2%


Analysis of Variance

Source           DF        SS      MS     F      P
Regression        1    244.35  244.35  3.30  0.071
Residual Error  188  13918.33   74.03
Total           189  14162.69
```

It is observed that the Gender *p*-value of 0.071 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Gender (i.e., Female vs. Male) is not a significant variable in the full model. Further, the standard deviation is s = 8.60428 with R^2 = 1.7% and R^2-adjusted = 1.2%, indicating the variable Gender explains virtually no variation in predicting average course grades.

RQ4: Is there a significant difference in average course grade between IET majors and other majors? The null hypothesis postulates no difference between the two group majors.

H_o: There is no difference in average course grades between majors
H_a: There is a difference in average course grades between majors

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 91.8 + 0.27 Major (X5)


Predictor     Coef  SE Coef      T      P
Constant    91.792    2.200  41.73  0.000
Major (X5)   0.270    1.863   0.15  0.885


S = 8.67900   R-Sq = 0.0%   R-Sq(adj) = 0.0%


Analysis of Variance

Source           DF        SS     MS     F      P
Regression        1      1.58   1.58  0.02  0.885
Residual Error  188  14161.10  75.33
Total           189  14162.69
```

It is observed that the Major *p*-value of 0.885 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Major (i.e., IET vs. Other) is not a significant variable in the full model. Further, the standard deviation is s = 8.67900 with R^2 = 0.0% and R^2-adjusted = 0.0%, indicating the variable Major explains no variation in predicting average course grades.

RQ5: Is there a significant difference in average course grade between Fall 2015 and Spring 2016 semesters? The null hypothesis postulates no difference between the two semesters.

H_o: There is no difference in average course grades between terms
H_a: There is a difference in average course grades between terms

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 94.2 - 1.38 Term (X3)


Predictor    Coef  SE Coef      T      P
Constant   94.209    2.019  46.67  0.000
Term (X3)  -1.384    1.257  -1.10  0.272


S = 8.65166   R-Sq = 0.6%   R-Sq(adj) = 0.1%


Analysis of Variance

Source           DF        SS     MS     F      P
Regression        1     90.67  90.67  1.21  0.272
Residual Error  188  14072.01  74.85
Total           189  14162.69
```

It is observed that the Term *p*-value of 0.272 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Term (i.e., Fall 2015 vs. Spring 2016) is not a significant variable in the full model. Further, the standard deviation is *s* = 8.65166 with R^2 = 0.6% and R^2-adjusted = 0.1%, indicating the variable Term explains essentially no variation in predicting average course grades.

RQ6: Is there a significant difference in average course grade among class standing (Freshmen, Sophomore, Junior, or Senior)? The null hypothesis postulates no difference among class standing.

H_o: There is no difference in average course grades among class standing
H_a: There is a difference in average course grades among class standing

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 80.7 + 2.95 Standing (X6)


Predictor        Coef  SE Coef      T      P
Constant       80.689    6.706  12.03  0.000
Standing (X6)   2.945    1.724   1.71  0.089


S = 8.61286   R-Sq = 1.5%   R-Sq(adj) = 1.0%


Analysis of Variance

Source           DF        SS      MS     F      P
Regression        1    216.58  216.58  2.92  0.089
Residual Error  188  13946.11   74.18
Total           189  14162.69
```

It is observed that the Standing *p*-value of 0.089 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Class Standing (Freshman, Sophomore, Junior, Senior) is not a significant variable in the full model. Further, the standard deviation is *s* = 8.61286 with R^2 = 1.5% and R^2-adjusted = 1.0%, indicating the variable Term explains virtually no variation in predicting average course grades.

RQ7: Is there a significant relationship between average course grade and cumulative grade point average?

H_o: There is no difference in average course grades among cumulative GPA
H_a: There is a difference in average course grades among cumulative GPA

Results are as follows:

```
The regression equation is
Course Avg. (Y) = 71.0 + 6.53 Cum.GPA (X7)


Predictor        Coef  SE Coef      T      P
Constant       71.006    3.699  19.20  0.000
Cum.GPA (X7)    6.529    1.131   5.77  0.000


S = 7.99921   R-Sq = 15.1%   R-Sq(adj) = 14.6%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       1   2133.1  2133.1  33.34  0.000
Residual Error  188  12029.6    64.0
Total           189  14162.7
```

It is observed that the Cum.GPA *p*-value of $0.000 < \alpha = 0.05$. Therefore, we reject H_o with 95% confidence and conclude that Cumulative Grade Point Average is a significant variable in the full model. Further, the standard deviation, s, is marginally reduced to $s = 7.99921$ with $R^2 = 15.1\%$ and R^2-adjusted = 14.6%, indicating the variable Cumulative GPA explains some variation in predicting average course grades.

It is important to note that both Standing (X6) and Cum.GPA (X7) were statistically significant variables in the Final Reduced Model with *p*-values of 0.041 and 0.000, respectively.

In sum, the researchers' primary objective was to determine which predictor variable(s), if any, had a significant effect on predicting average course grades. The Final Reduced Model is: Course Average ($\hat{y}$) = 58.051 + 3.276 Standing (X6) + 6.611 Cum. GPA(X7).

Beginning with seven main effect predictor variables, at the $\alpha = 0.05$ significance level, only two predictor variables, Class Standing and Cumulative GPA, proved statistically significant. All higher-order interaction terms were removed from the full model since none of the terms proved significant.

The R^2 value of 17.0% and correlation coefficient, $r = 41.2\%$, clearly indicate room for improvement in the final reduced model. Perhaps consideration of other main effect variables not included in the current model may contribute to higher R^2 and r values.

6. AREAS OF FUTURE STUDY

This study consists of analyzing average course grades in seven different courses using the same technology by the same professor at the same four-year comprehensive university during the Fall and Spring semesters in one recent academic year. Future studies could include a replication of this study during the next academic year; an analysis of average course grades by other professors within the same department at the same four-year comprehensive university; an analysis of average course grades by other professors in different departments at the same four-year comprehensive university; a comparative analysis between undergraduate- and graduate-level converged courses, as well as conducting similar analyses involving professors from other universities who also utilize converged classroom learning environments.

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