Analyzing Course Grades in a Converged Classroom Environment – A Follow-Up Study

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Two significant questions in evaluating student course grades in a converged classroom environment include whether an empirical model can be developed to accurately predict students' average course grades and whether course grades differ between on-campus students vs. distance students. The purpose of this study is to validate the results of a previous study with new data, including course grades for four different industrial engineering technology courses taught by the same professor during one full academic year. In sum, the reduced model (with new data) becomes the same two-factor main effects only regression model that was developed in the initial study.

INTRODUCTION

The converged classroom combines both hybrid (i.e., on-campus) and online learning environments during the same Live class session. Unlike traditional courses that meet face-to-face two or three times per week, hybrid sections of the course meet one day per week on campus and have pre-recorded course lectures and materials such as narrated Powerpoint slides, an Overview Page, videos, handouts, 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, Overview pages, videos, handouts, assignments, and exams as for the hybrid students.

All converged courses are developed to include a 50% pre-recorded lecture video (i.e., pre-recorded lecture or the narrated Powerpoint slides) and a 50% Live Session component that meets one day per week. 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 selecting the Recordings tab and 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 course grades in four different Industrial Engineering Technology (IET) courses during the 2016-17 academic year utilizing the same Blackboard Collaborate^{TM} converged classroom technology and taught by the same professor. Several research questions (RQ) in this follow-up study 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 objective of this research is to validate the predictive model results of the initial study from the 2015-16 academic year (Keyser & Parvathareddy, 2017) by determining which main effect predictor variable(s), if any, have a significant effect on predicting course grades. This will be addressed by forming a reduced regression model that is originally based on a 7 main effect factor 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) due to many advantages it provides over traditional classroom courses. 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). In higher education, online enrollments have grown 21% vs. 2% enrollment growth for traditional classroom courses n s 2002 (Allen & Seaman, 2007).

Despite the many advantages of online learning, notable issues include a feeling of isolation by online students (Brown, 1996), students who may be confused about the instructions or where to find course elements (Hara & Kling, 2000), and a reduction in level of student interest and learning effectiveness (R. Maki, W. Maki, Patterson, & Whittaker, 2000).

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' course grades for four different Industrial Engineering Technology (IET) converged courses taught in the Fall and Spring semesters of the 2016-17 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-listed to fit other particular major requirements. For example, business majors were permitted to register for IET 2227 – Introduction to Statistics to satisfy their Intro to Statistics requirement.

All four courses in this study are converged classroom courses, meaning each course consists of a hybrid (i.e., on-campus) section as well as an online section. Both sections are synchronized so that both hybrid and online students may simultaneously attend the Live Session. The Blackboard Collaborate™ 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 four courses were taught by the same professor utilizing the same classroom technology, specifically, Desire2Learn™ and Blackboard Collaborate™.

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 in the Assignments tab in the D2L NavBar 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, 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 semesters.

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, 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-F 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 course grade for each student is determined and a letter grade is posted in the Grades tab for each student in the course.

In this study, the full model is based on all 7 main effects since all two-factor and higher-order terms proved insignificant in the initial study.

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

Response variable:

$\hat{y}$ = Course Grade

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 2016; 2 = Spring 2017)
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 researcher addressed the research questions provided in the Introduction section.

Reaching the final reduced model employs a two-step process. (1) Once the full model is analyzed and p-values for all variables are compared to the researchers’ desired significance level, $\alpha = 0.05$, (2) a reduced model was formed that retained only statistically significant predictor variables. A series of diagnostic tests, including an analysis of residuals, follows to test its validity of the reduced model in predicting average course grades.

RESEARCH FINDINGS

The participants in this study include students at a four-year comprehensive university who enrolled in converged Industrial Engineering Technology (IET) courses (i.e., including on-campus (hybrid) and distance (online) students during the Live lecture session). The same professor taught these IET courses using the same online classroom delivery technology (Blackboard Collaborate™ online classroom technology in the Desire2Learn™ (D2L) online learning environment during the Fall 2016/Spring 2017 academic year. In keeping with the principle of parsimony as in the initial study, the results for the full model are shown below.

(1) Full Model:

```
Regression Equation
Course Grade (Y)  =  -0.814929 - 0.0870911 Gender (X1) + 0.0788999 Age Group
                     (X2) + 0.0119332 Term (X3) - 0.0354078 Registration (X4) -
                     0.321919 Major (X5) + 0.533686 Standing (X6) + 0.830711
                     Cum.GPA (X7)
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Coefficients

Term	Coef	SE Coef	T	P
Constant	-0.814929	0.876953	-0.92927	0.355
Gender (X1)	-0.087091	0.142857	-0.60964	0.543
Age Group (X2)	0.078900	0.097033	0.81313	0.418
Term (X3)	0.011933	0.163296	0.07308	0.942
Registration (X4)	-0.035408	0.124344	-0.28476	0.776
Major (X5)	-0.321919	0.338884	-0.94994	0.344
Standing (X6)	0.533686	0.140616	3.79535	0.000
Cum.GPA (X7)	0.830711	0.114424	7.25996	0.000

Summary of Model

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S = 0.640811     R-Sq = 48.67%         R-Sq(adj) = 45.46%
PRESS = 52.5817  R-Sq(pred) = 41.31%
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Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	7	43.6001	43.6001	6.2286	15.1680	0.000000
Gender (X1)	1	7.3502	0.1526	0.1526	0.3717	0.543335
Age Group (X2)	1	2.1101	0.2715	0.2715	0.6612	0.417871
Term (X3)	1	2.6680	0.0022	0.0022	0.0053	0.941875
Registration (X4)	1	1.1927	0.0333	0.0333	0.0811	0.776356
Major (X5)	1	1.9622	0.3706	0.3706	0.9024	0.344188
Standing (X6)	1	6.6734	5.9151	5.9151	14.4047	0.000240
Cum.GPA (X7)	1	21.6436	21.6436	21.6436	52.7071	0.000000
Error	112	45.9916	45.9916	0.4106		
Lack-of-Fit	102	41.4916	41.4916	0.4068	0.9040	0.635204
Pure Error	10	4.5000	4.5000	0.4500		
Total	119	89.5917				

The full model contains both significant terms whose *p*-values ≤ 0.05 and non-significant main effect terms whose *p*-values > 0.05.

The regression equation for the Full Model is:

$\hat{y}$ = -0.815 – 0.087 Gender (X1) + 0.079 Age Group (X2) + 0.012 Term (X3) – 0.035 Registration (X4) – 0.322 Major (X5) + 0.534 Standing (X6) + 0.831 Cum. GPA (X7)

A quick general overview of these results reveal some important conclusions:

1) R^2 = 48.67%, indicating a moderate amount of variation in the full model is explained by the variables in the full model;
2) R^2-adjusted decreased slightly to 45.46%, meaning the variation in predicting course grades decreased slightly 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 at the $\alpha = 0.05$ level of significance;

4) In fact, two main effect variables, Class Standing (X6) and CumGPA (X7) appear to be statistically significant at $\alpha = 0.05$, *as they relate to other variables* in the full model, and should be retained to form the reduced model.

(2) Reduced Model:

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 are as follows:

```
Regression Equation
Course Grade (Y)  =  -1.52397 + 0.575674 Standing (X6) + 0.875555 Cum.GPA (X7)

Coefficients
Term                Coef   SE Coef         T      P
Constant        -1.52397  0.523040  -2.91368  0.004
Standing (X6)    0.57567  0.124432   4.62641  0.000
Cum.GPA (X7)     0.87556  0.102678   8.52721  0.000

Summary of Model

S = 0.632276     R-Sq = 47.79%        R-Sq(adj) = 46.90%
PRESS = 49.0856  R-Sq(pred) = 45.21%

Analysis of Variance
Source            DF   Seq SS   Adj SS   Adj MS        F          P
Regression         2  42.8182  42.8182  21.4091  53.5530  0.000000
  Standing (X6)    1  13.7493   8.5566   8.5566  21.4036  0.000010
  Cum.GPA (X7)     1  29.0689  29.0689  29.0689  72.7133  0.000000
Error            117  46.7735  46.7735   0.3998
  Lack-of-Fit     89  37.6068  37.6068   0.4225   1.2907  0.224671
  Pure Error      28   9.1667   9.1667   0.3274
Total            119  89.5917
```

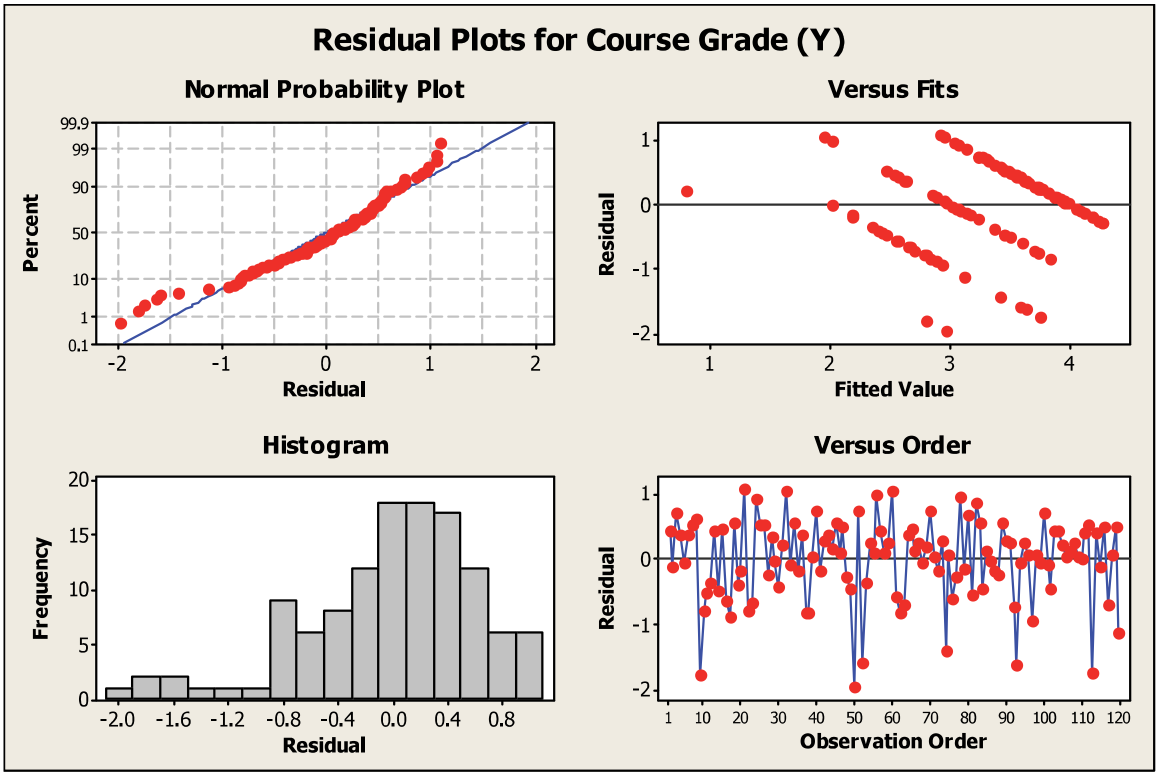
At the $\alpha = 0.05$ level of significance, the reduced model is significant (*p*-value = 0.0000) and both terms in the reduced model are statistically significant (*p*-values < $\alpha = 0.05$). The standard deviation is s = 0.632276 and R^2 = 47.79%, a reduction of only 0.88% from the full model, a clear signal that the other terms in the model were non-significant towards predicting course grades.

The final reduced model becomes: Course Grade (Y) = -1.52397 + 0.575674 Standing (X6) + 0.875555 Cum.GPA (X7).

Next, diagnostic procedures were applied, including a residuals analysis, to determine whether the residuals have appear independent and have constant variance. We begin with a Four-in-One plot of the residuals for Course Grades in Figure 1, which includes a Normal Probability Plot; a Histogram of Residuals; Residuals plotted against Fitted Values; and Residuals plotted in Observation Order.

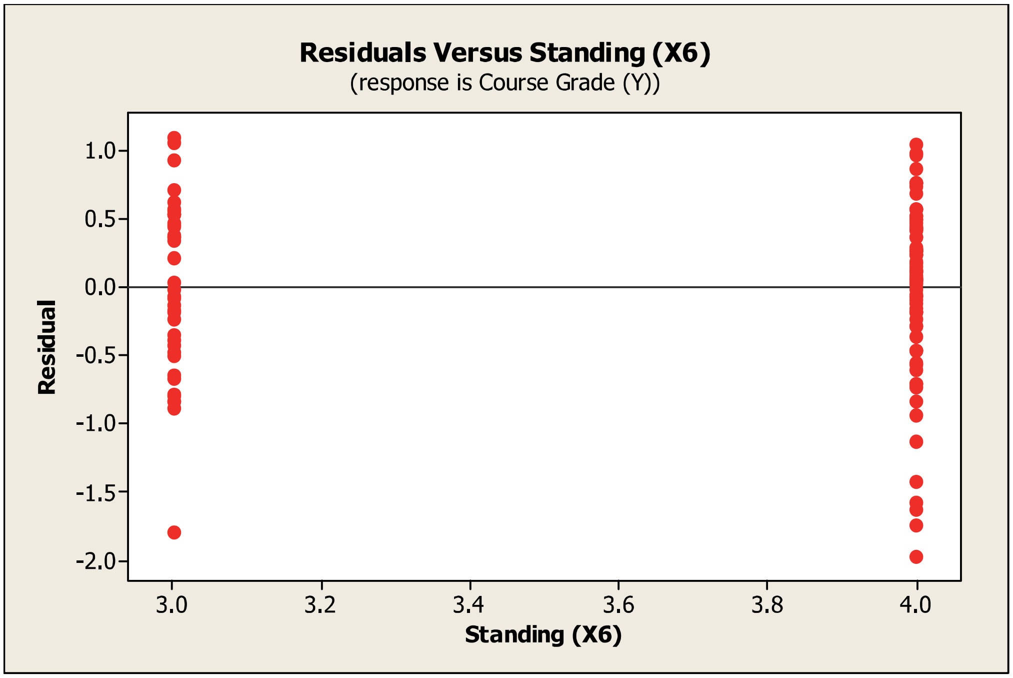
The Normal Probability Plot of residuals for Course Grade reveals non-normality, as indicated by the tails at both extremes of the plot, although there is some semblance of normality in the middle portion of the plot. The Histogram of residuals corroborates what we see in the Normal Probability Plot; 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 for Course Grade display non-constant variance. The residuals plotted in observation order reveals random variability in the data. Since the data are not time-ordered data, the presence of multicollinearity is not apparent.

FIGURE 1
A FOUR-IN-ONE DIAGRAM OF RESIDUALS FOR COURSE GRADE (Y)



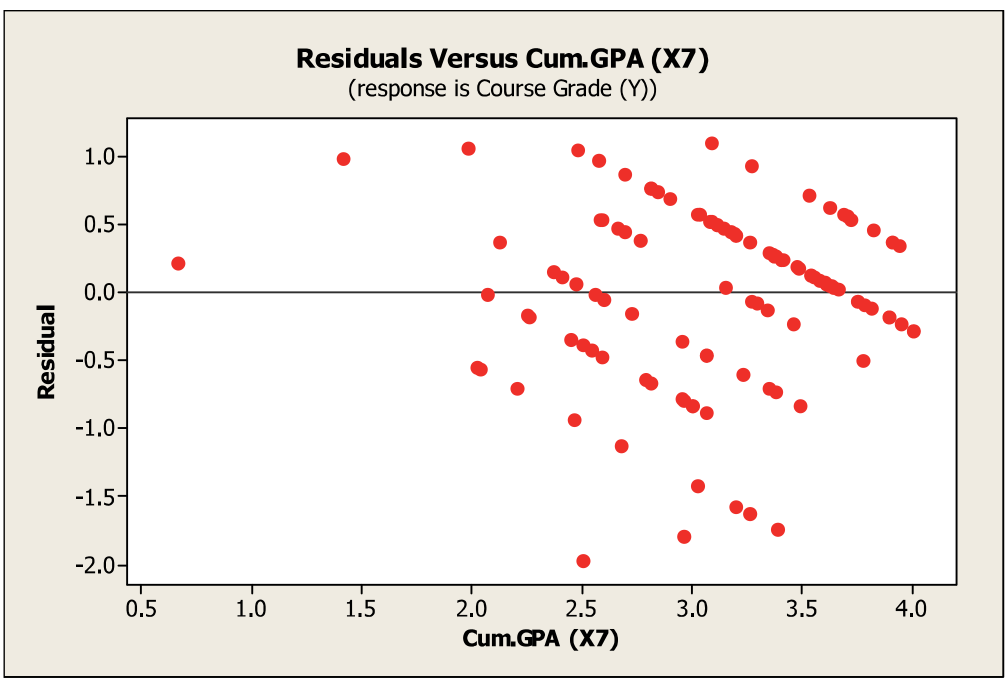
The Residuals vs. Fitted plot for the predictor variable, Standing (X6), is shown in Figure 2 below. The variance has approximately the same overall variance between the two values (3 = Junior class standing; 4 = Senior class standing) leading one to assume constant variance among all residuals, although the residuals appear more tightly clustered for Junior class standing than for Senior class standing.

FIGURE 2
A RESIDUALS VS. FITTED PLOT FOR (CLASS) STANDING (X6)



The Residuals vs. Fitted plot for the predictor variable, Cumulative GPA, is shown in Figure 3. There appears to be constant variance among residuals in this plot.

FIGURE 3
A RESIDUALS VS. FITTED PLOT FOR CUMULATIVE GPA (X7)



Final analysis of the Reduced Model ANOVA table shows the p-values for both Standing and Cumulative GPA < $\alpha = 0.05$, leading to the conclusion that the remaining two predictor variables are statistically significant. Further, the standard deviation is $s = 0.632276$ and $R^2 = 47.79\%$, indicating that 47.79% of the variability in the response variable, $\hat{y}$, is explained by the two predictor variables, Class Standing and Cumulative GPA.

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 studentsIt is observed that the Registration p-value of 0.776 > $\alpha = 0.05$ in the full model. 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, indicating the predictor variable Registration explains no variation in predicting student course grades in relation to all other predictor variables.

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

It is observed that the Age Group p-value of 0.418 > $\alpha = 0.05$. 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, indicating the predictor variable Age Group explains virtually no variation in predicting student course grades in relation to all other predictor variables.

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

It is observed that the Gender p-value of 0.543 > $\alpha = 0.05$. 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, indicating the predictor variable Gender explains virtually no variation in predicting student course grades in relation to all other predictor variables.

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

It is observed that the Major p-value of 0.344 > $\alpha = 0.05$. 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, indicating the predictor variable Major explains virtually no variation in predicting student course grades in relation to all other predictor variables.

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

It is observed that the Term p-value of 0.942 > $\alpha = 0.05$. Therefore, we fail to reject H_o with 95% confidence and conclude that Term (i.e., Fall 2016 vs. Spring 2017) is not a significant variable in the full model, indicating the predictor variable Term explains virtually no variation in predicting student course grades in relation to all other predictor variables.

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

It is observed that the Standing *p*-value of $0.000 < \alpha = 0.05$. Therefore, we reject H_o with 95% confidence and conclude that Class Standing (Freshman, Sophomore, Junior, Senior) is a significant variable in the full model, indicating the predictor variable (Class) Standing does, indeed, explain variation in predicting average course grades in relation to all other predictor variables.

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

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 Cum.GPA (0 – 4.0) is a significant variable in the full model, indicating the predictor variable Cum.GPA does, indeed, explain variation in predicting average course grades in relation to all other predictor variables.

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 0.000 and 0.000, respectively.

In sum, the researchers' objective was to validate the results of the previous, or initial, study in determining which predictor variable(s), if any, had a significant effect on predicting average course grades. The Reduced Model is: Course Grade (Y) = -1.52397 + 0.575674 Standing (X6) + 0.875555 Cum.GPA (X7).

Beginning with seven main effect predictor variables, only two predictor variables, Class Standing and Cumulative GPA, proved statistically significant. All higher-order interaction terms were removed from the full model 1) in keeping with the principle of parsimony, and 2) since none of these higher-order terms proved significant in the initial study.

The R^2 value of 47.79% was much improved over the R^2 value of 17.0% in the initial study. Consideration of other main effect variables not included in the current full model may contribute to higher R^2 and *r* values.

In conclusion, the Reduced Model discovered in this follow-up study is the identical model concluded by the researchers in the initial study (Keyser & Parvathareddy, 2017) during the previous year. Therefore, the conclusion in the initial study is validated.

AREAS OF FUTURE STUDY

This study consists of analyzing student course grades in four different courses using the same technology by the same professor at the same four-year comprehensive university during the 2016-17 Fall and Spring semesters. The next study will compare student course grades between students majoring in industrial engineering technology vs. students majoring in industrial & systems engineering taught by the same professor within the same department at the same four-year comprehensive university. Additional future studies could include 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.

REFERENCES

Allen, I. E., & Seaman, J. (2010). *Class differences: Online education in the United States, 2010.* Needham, MA: Babson Survey Research Group.

Allen, I. E., & Seaman, J. (2007). Online nation: Five years of growth in online learning. Needham, MA: Sloan Consortium. Retrieved from http://sloanconsortium.org/publications/survey/pdf/online_nation.pdf

Ary, E. J., & Brune, C. W. (2011). A comparison of student learning outcomes in traditional and online personal finance courses. *MERLOT Journal of Online Learning and Teaching*, 7, 465-474.

Aslanian, C. (2001). You're never too old: Excerpts from adult students today. *Community College Journal*, 71, 56-58.

Blier, H. M. (2008). Webbing the common good: Virtual environment, incarnated community, and education for the Reign of God. *Teaching Theology and Religion*, 11, 24-31. doi:10.1111/j.14679647.2007.00393.x

Bonakdarian, E., Whittaker, T., & Yang, Y. (2010). Mixing it up – more experiments in hybrid learning. *Journal of Computing Sciences in Colleges*, 25(4), 97-103.

Brown, K. M. (1996). The role of internal and external factors in the discontinuation of off-campus students. *Distance Education*, 17, 14-71.

El Mansour, B., & Mupinga, D. M. (2007). Students' positive and negative experiences in hybrid and online classes. *College Student Journal*, 41, 242-248.

Hackbarth, W. (1996). *The educational technology handbook: A comprehensive guide*. Englewood Cliffs, NJ: Educational Technology Publications.

Hara N., & Kling, R. (2000). Students' distress with a web-based distance education course: An ethnographic study of participants' experiences. *Information, Communication, and Society*, 3, 557-559.

Harasim, L. M. (1990). *Online education: Perspectives on a new environment*. New York: Praeger.

Lam, M. (2009). Effectiveness of web-based courses on technical learning. *Journal of Education for Business*, 6, 323-331.

Keyser, R. & Parvathareddy, H. (2017). An Assessment of Average Course Grades in a Converged Classroom Environment. *Journal of Higher Education Theory & Practice*, 17(3), 70-86.

Kiser, K. (1999). 10 things we know so far about online training. *Training*, 36, 66-74.

Kolb, D. A. (1984). *Experiential learning: Experience as the source of learning and development*. Upper Saddle River, NJ: Prentice Hall.

Knowles, M. (1980). *The modern practice of adult education: From pedagogy to andragogy* (2nd ed.). New York, NY: Cambridge Books.

Knowles, M. (1990). *The adult learner: a neglected species* (4th ed.). Houston, TX: Gulf Publishing.

Maki, R. H., Maki, W. S., Patterson, M., & Whittaker, P. D. (2000). Evaluation of a web-based introductory psychology course: I. Learning and satisfaction in on-line versus lecture courses. *Behavior Research Methods, Instruments and Computers*, 32, 230-239.

Matthews, D. (1999). The origins of distance education and its use in the United States. *THE Journal*, 27(2), 54-66.

Swan, K., Shea, P., Frederickson, E., Pickett, A., Pelz, W., & Maher, G. (2000). Building knowledge-building communities: Consistency, contact, and communication in the virtual classroom. *Journal of Educational Computing Research*, 23(4), 389-413.

Van Tassel, J. & Schmitz, J. (2013). Enhancing learning in the virtual classroom, *Journal of Research in Innovative Teaching*, 6(1), 37-53.

Wiles, G. & Keyser, R. (2016). Converged classroom approval based on student satisfaction. *Journal of Higher Education Theory and Practice*, 16(3), 17-21.

Wilson, D., & Allen, D. (2014). Success rates of online versus traditional college students, *Research in Higher Education*, 14, 1-8.

Wood, S. L. (2010). Technology for teaching and learning: Moodle as a tool for higher education. *International Journal of Teaching and Learning in Higher Education*, 22(3), 299-307.
Woodworth, P., Applin, A. G. (2007). A hybrid structure for the introductory computers and information technology course. *The Journal of Computing Science in Colleges*, 22(3), 136-144.
Xu, D., & Jaggars, S. S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas, *Journal of Higher Education*, 85(5), 633-659.
Yudko, E., Hirokawa, R., & Chi, R. (2008). Attitudes, beliefs, and attendance in a hybrid course. *Computers & Education*, 50, 1217-1227. doi: 10.1016/j.compedu.2006.11.005