AC 2011-1670: PARTICIPATION, CLASS TYPES, AND STUDENT PERFORMANCE IN BLENDED-LEARNING FORMAT

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Virtual Attendance, Class Types, and Student Performance in Blended Learning Format

Abstract

For the last century, the trend towards blended-learning as a preferred instructional strategy has gained increased momentum. "Blended-learning systems combine face-to-face instruction with computer-mediated instructions" (Graham, 2005). As Shibley (2010) pointed out, "A blended course involves a mixture of face-to-face activities with online activities," and "Usually face-to-face time is reduced by 50% but reductions range from 10% - 90%" (Shibley, 2010). One of the major advantages of blended-learning is to maximize student mobility in a vibrant technology and socio-economic environment.

For traditional classroom teaching, there were abundant research studies revealing that the classroom attendance had a positive impact on academic performance. However, there have been less explorations of the correlation between online attendance and student learning performance (Douglas, 2008). This research was to address the question whether there were significant differences between the three levels (low, adequate, and high) of virtual attendance in newly implemented blended-learning classes, in regard to students' academic performance measured by the end-of-term overall scores.

The research resulted in significant findings between different levels of e-learning attendance in regard to students' end-of-term overall scores in blended-learning format. The statistical results asserted that for both programming and English classes, the virtual attendance in various e-learning activities played a critical role in student performance. The pre-planned and correlation tests revealed that, for students enrolled in different types of classes delivered in blended-learning format, the level of virtual attendance served as a strong predictor of students' end-of-term overall grades.

The significance of this research is to emphasize the importance of virtual attendance in blended-learning process. Benefiting from the effective prediction of students' success based on their level of attendance, the findings in this research will help students themselves, student academic advisors, student finance advisors, professors, and academic administrators, to closely monitor all students' onsite and virtual attendance records in blended-learning classes. Reducing every single failure in every single class can speed up student's degree-completion by a time increment, resulting in a reduction in student tuition and fees, improving the time-to-degree cycles, help student's entrance into

the labor market faster, and substantially increase student's life-time earnings (Crede et al., 2010).

Introduction

Since 1990s, especially after the turn of the new millennium, blended-learning as a new instructional delivery format has gained fast acceptance in higher education. Tippe (2006) observed that student learning performance and faculty teaching effectiveness were both improved in his engineering technology course taught in blended-learning approach; the successful delivery of the blended-learning course resulted in better student and faculty satisfaction. Research in applied programming and elementary calculus classes also demonstrated that blended-learning provided students with greater controllability over their learning process and enhanced students learning persistence (Deperlioglu & Kose, 2010; Naidoo & Naidoo, 2007).

In a meta-analysis prepared for the U.S. Department of Education, the authors concluded that "Instruction combining online and face-to-face elements had a larger advantage relative to purely face-to-face instruction than did purely online instruction. The mean effect size in studies comparing blended with face-to-face instruction was +0.35, $p < .001$. This effect size is larger than that for studies comparing purely online and purely face-to-face conditions, which had an average effect size of +0.14, $p < .05$" (U.S. Department of Education, 2009). In the same meta-analysis, the authors further stated, "Hence, the observed advantage for online learning in general, and blended learning conditions in particular, is not necessarily rooted in the media used per se and may reflect differences in content, pedagogy and learning time" (U.S. Department of Education, 2009).

The essence of blended-learning is to provide enriched e-learning and virtual classroom interactive activities in addition to an existing traditional face-to-face instructional environment. "Blended-learning systems combine face-to-face instruction with computer-mediated instructions" (Graham, 2005). As Shibley (2010) pointed out, "A blended course involves a mixture of face-to-face activities with online activities," and "Usually face-to-face time is reduced by 50% but reductions range from 10% - 90%" (Shibley, 2010). One of the major advantages of blended-learning is to maximize student mobility in a vibrant technology and socio-economic environment.

For traditional classroom teaching, there were abundant research studies revealing that the classroom attendance had a positive impact on academic performance. In reporting a meta-analysis, Credé, Roch, & Kieszczynka (2010) concluded that there were strong correlations between classroom attendance and students' grades ($k = 69$, $N = 21{,}195$, $\rho = .44$) and GPAs ($k = 33$, $N = 9{,} 243$, $\rho = .41$). In the same meta-analysis, Credé et al. studied a substantial number of research articles, dissertations, and papers over a time-length of 82 years, and arrived at the conclusion that "These relationships make class attendance a better predictor of college grades than any other known predictor of academic performance, including scores on standardized admissions tests such as the SAT, high school GPA, study habits, and study skills" (Credé, Roch, & Kieszczynka, 2010). Credé et al. (2010) further reported that the strong correlation between attendance and students' grades did not demonstrate decrease over the length of 82 years; even during the past century when instructional delivery modes were increasingly adopting online components, the attendance was still playing a critical part for students to achieve better grades (Crede et al., 2010).

According to Crede et al. (2010), "As currently measured by most researchers, **class attendance simply denotes physical presence in the classroom**." For many colleges and universities, taking regular attendance in classes with high enrollment is tricky (Stephenson, 1994), and could sometimes be inaccurate. On the other hand, in a classroom setting, even though a student may be physically attending, she or he may be absent-minded, preoccupied, or may be mentally "day-dreaming."

Currently different researchers report different ways to measure virtual attendance, including the login time in e-learning components, and the frequency of "mouse" clicks. As researchers assert, in attending e-learning activities, there is far less pressure from the instructor on students to pretend to be in "presence." Therefore, students' virtual attendance may be recorded more accurately than taking traditional classroom attendance. With online tools and technology, the attendance-taking becomes less a burden for instructors to determine the attendance data (Crede et al., 2010).

While there is a substantial amount of research on the correlation between attendance on student learning outcomes, there has been less exploration of the correlation between online attendance and student learning performance (Douglas, 2008); the intuitive belief is that the virtual attendance in e-learning activities in blended-learning format is of equal importance as face-to-face learning, if not more critical. The fast-growing pace of blended-learning delivery trend necessitates the need for quantifying the impact of different levels of virtual attendance in e-learning activities on students' performance.

In blended-learning format, the e-learning activities include the following components:

1. Instructor-led threaded discussions
2. Internet-based e-books
3. Online or tele-Q & A sessions
4. Virtual document sharing
5. Internet-based Webiography
6. Web-based practice quizzes and tests
7. Web-based laboratory exercises
8. Web-based homework exercises
9. Web-based grade-books with feedback commentary areas
10. Web-based examination

Each component contains a set of well-defined learning activities. Based on web technology, students' attendance in each of the above components is automatically recorded in terms of the frequency and time length. For blended-learning courses using web-based virtual instructional platform, students' attendance in terms of time length is automatically recorded for their time spent in Course Home, each week, and the Course

Tools. A sample attendance record in the virtual platform "User Activities" exported to Excel spreadsheet is shown in Table 1 (all values are random numbers in minutes):

Table 1. A Sample Attendance Record Exported to Excel Spreadsheet (all values are random numbers in minutes)

Name	Course Home	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Course Tools	Total
Teacher	288	329	107	98	108	126	96	64	60	1757	3033
Student 1	322	413	175	244	245	100	105	30	5	437	2076
…	388	603	541	195	941	560	520	305	2	1459	5514
Student N	210	353	239	221	428	316	333	447	4	1021	3572

Course Tools contain different components of virtual learning tools and the places for students to turn in their work. The Course Home contains the components course information, syllabus, and internet-based laboratory exercises. The Weekly tasks include weekly course goals, homework assignments, lecture, discussions, and tests. The time values depict the time-length faculty and each student spend in each component, in terms of minutes. Since the classes are "blended" in nature, students may spend little time in Week 8, due to the fact that they are taking final exams in a physical classroom setting.

The Definition of Instructional Hour. The fundamental definition of a "credit hour" is based on the notion of a single hour of instructional time every week over a defined instructional period, such as an academic term, or an academic semester (Ewell, 2004). Although there is no strict regulation by the U.S. Department of Education as how many actual instructional minutes constitute one credit hour, common accreditation practice assumes that the credit hour definition was to provide higher education institutions with a reference instead of a numeric time quantity. However, a majority of colleges and universities considers one instructional hour as 50 clock minutes. Under laboratory settings, one credit hour may require two or more clock hours of lab-work per week. The quantitative measurement of an instructional hour used in this study follows the above consideration employed by the majority of colleges and universities.

Different Levels of Virtual Attendance. Based on the fundamental definition of "credit hour" and the common practice across colleges and universities, the definitions of the different levels of virtual attendance used in this research were as follows.

Since the English-writing class was a 4-credit/4-contact blended-learning course with 50% onsite and 50% online design, which was delivered in an 8-week academic session with final exam arranged at the end of the session, students were expected to attend no less than 30 hours of face-to-face activities and 30 hours of virtual learning activities; each hour was consisted of 50 clock minutes,. Therefore, for the English-writing class, a virtual attendance below 29.9 hours was defined as low attendance; a virtual attendance between 30 hours to 59.9 hours was defined as adequate attendance; a virtual attendance above 60 hours was defined as high attendance.

Similarly, since the programming class was a 4-credit/5-contact blended-learning course with 50% onsite and 50% online design over an 8-week session with final exam at the end of the session, students were expected to attend no less than 37.5 hours of face-to-face activities and 37.5 hours of virtual learning activities. Therefore, for the programming class, a virtual attendance below 37.4 hours was defined as low attendance; a virtual attendance between 37.5 hours to 75 hours was defined as adequate attendance; a virtual attendance above 75 hours was defined as high attendance.

End-of-Term Overall Scores. Traditionally, student academic performance is measured by a wide range of indicators, which reflect how much they accomplish after certain learning processes. According to Checchi, Franzoni, Ichino, and Rustichini (1999), academic performance is considered as the amount of human capital obtained during students' academic career, which includes "both elements of quantity and quality" (p. 2).

For a class offered in blended-learning format, students' end-of-term overall scores are composed of the calculated assessment of both onsite and online quality and quantity of performance based on the weighted weekly and daily individual sub-scores.

Comprehensive grading rubrics are usually defined, structured, and established for each e-learning and on-site learning activity to assess the quantity and quality of students' work. Table 2 demonstrates an overall itemized grading summary at the end of the term, with automatically calculated end-of-term overall grades (all values are random numbers).

This research is to address the question whether there are significant differences between the three levels (low, adequate, and high) of e-learning attendance in newly implemented blended-learning classes, in regard to students' academic performance measured by the end-of-term overall scores. The research statistically compared the academic performance of students in a structured-programming class in an engineering technology curriculum and in an English composition class, both taught in blended-learning format.

Table 2. Overall Itemized Grading Summary with Random Numbers

Student Name	Item Summary - Assignments	Item Summary - Discussion	Item Summary - Final Exam	Item Summary - iLab	Item Summary - Quiz	Course Points to Date	Points Possible to Date	Course Average to Date
	170	210	220	113.5	170	883.5	1000	88.35%
	98	110	156	105.5	165	634.5	1000	63.45%
	120	180	231	98	150	779	1000	77.90%
	184	213	180	110	190	877	1000	87.70%
	180	205	245	110	205	945	1000	94.50%
	180	200	195	100	160	835	1000	83.50%
	132.5	210	217	88	115	762.5	1000	76.25%

The study used 3X2 factorial and one-way analyses of variance, Kruskal-Wallis test, *t*-tests, correlation analysis, and Games-Howell *Post Hoc* tests to explore the differences among different levels of e-learning attendance, and between students in applied programming and English composition classes, in blended-learning delivery format, in regard to their end-of-term overall scores. The actual sample was collected from an engineering technology programming class and an English composition class, both taught in the newly deployed blended-learning format, in a four-year baccalaureate program.

The research resulted in significant findings between different levels of e-learning attendance, in regard to students' end-of-term overall scores in blended-learning format. The statistical results reclaimed that for both programming and English classes, the virtual attendance in various e-learning activities played a critical role in student performance. The pre-planned and correlation tests revealed that, for students enrolled in both applied programming and in English writing classes delivered in blended-learning format, the level of e-learning attendance served as a strong predictor of students' end-of-term overall grades.

The significance of this research is to emphasize the importance of virtual attendance in blended-learning process. Due to the effective prediction of students' success based on their level of attendance, the findings in this research will benefit students themselves, student academic advisors, student finance advisors, professors, and academic administrators, to closely monitor all students' onsite and virtual attendance records in blended-learning classes. Every step of improvement makes a contribution to the end-result accumulatively. Reducing every single failure in every single class can speed up student's degree-completion by a time increment, resulting in a reduction in student tuition and fees, improving the time-to-degree cycles, help student's entrance into the labor market faster, and substantially increase student's life-time earnings (Crede et al., 2010). This is the ultimate goal of the career-focused universities. This research advocates improved preparation for implementing blended-learning process to enhance engineering and technology education.

Research Questions

The main research questions are listed as follows.

Research Question 1. Is there an *interaction* of students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities and the types of classes they are taking (applied-programming class versus English-writing class), in regard to their end-of-term overall scores in blended-learning format?

Research Question 2. Are there statistically significant differences among students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to their end-of-term overall scores in blended-learning format?

Research Question 3. Is there statistically significant difference between students taking programming class, and students taking English-writing class, in regard to their end-of-term overall scores in blended-learning format?

Research Question 4. Is there a significant correlation between virtual attendance in e-learning and students' end-of-term overall scores in blended-learning classes? What is the predictive model describing the effects of attendance on student performance?

Research Question 5. Are there statistically significant differences among students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to the percentage of student whose end-of-term overall scores were in the AB range, and in regard to the percentage of student whose end-of-term overall scores were in the DF range?

Methodology

Variables. In Research Qustions 1, 2, and 3, there were two independent variables. The first independent variable, the students' level of virtual attendance in e-learning activities, had three categorical values. The first category was the group of students who had the low-level of attendance (participated fewer than marginal time required); the second category was the group of students who had the adequate level of attendance; the third category was the group of students who had high-level attendance in e-learning activities. The second independent variable, the type of freshman classes, had two categories. The first category was the freshman applied-programming class, and the second category was the freshman English-writing class, both were offered in blended-learning format. The dependent variable was students' overall scores earned at the end of the academic term. The overall scores were combinations of weekly assessment of the frequency and quality of e-learning activities, weekly quizzes and tests, on-site and online homework, the project assignments, and the grades earned for the midterm and final exams.
In Research Question 4, the independent variable was students' virtual attendance in terms of time measures, and the dependence variable was students' end-of-term overall grades. Both variables were assumed as scale values.

In Research Question 5, the independent variable had three categorical values describing students' levels of attendance, while the dependent variables were students' overall performance in terms of AB and DF rates.

Data Analysis and Research Design. For Research Questions 1, 2, and 3, the overall research type was 3X2 factorial design, since in the research questions there were three categories for the first independent variable (low-level attendance, adequate attendance, and high-level attendance) and two categories for the second independent variable (programming class and English-writing class). The dependent variable was assumed as near-normally distributed data. Based on the data types, it was appropriate to use 3X2 two-way factorial ANOVA as the inferential statistic (Morgan, Leech, Gloeckner, & Barrett, 2004).

The research first investigated if the first independent variable (level of attendance in e-learning) and the second independent variable (type of freshman classes) interacted, in regard to the dependent variable. It then examined the main effects of the level of attendance in e-learning, and the type of freshman classes on students' end-of-term overall final scores.

The research found that the interaction was insignificant. One-way ANOVA, Kruskal-Wallis test, Games-Howell *Post Hoc* tests, pre-planned Mann-Whitney U tests and pre-planned *t*-tests were used to run the post hoc analysis to compare the significant differences in order to reach and verify the final conclusions. After the statistical results were obtained, the confidence intervals, effect sizes, and the direction of the effect and the direction of the correlation results were discussed.

For the rest of the research questions, based on the variable characteristics, Pearson correlation test, descriptive statistical methods, and curve-fitting modeling techniques were used to derive research findings.

Findings

Research Question 1. The first research question contained two independent variables. The first independent variable had three categories, while the second independent variable had two categories. The dependent variable was students' end-of-term overall scores in the blended learning classes.

Two-way ANOVA (analyses of variance) was executed to determine whether there were significant interaction and/or significant differences among the three levels of e-learning attendance and two types of freshman classes.

The two-way ANOVA test showed that there was not a significant interaction effect of the level of attendance and the type of the freshman classes in regard to students' overall scores. Table 3 shows the means and standard deviations among the levels of e-learning attendance by the type of freshman classes, in regard to students' end-of-term overall scores.

Two-way ANOVA showed that there was an overall significant difference among the levels of low, adequate, and high attendance in e-learning activities, $F\ (2, 137) = 14.01$. This significant result will be further discussed in the later part of this paper. Meanwhile, there was not a significant difference identified between the freshman programming class and the English-writing class.

Research Question 2. The second research question contained the first main independent variable, the level of e-learning attendance, which had three categories.

As being discussed above, there was an overall significant difference among the levels of low, adequate, and high attendance in e-learning activities in regard to students' overall scores.

Table 3
Means and Standard Deviations among the Levels of E-Learning Attendance by the Type of Freshman Classes for Students' Overall Scores

	Programming Class			English-Writing Class			Total	
Level of Attendance	*M (%)*	*SD*	*n*	*M(%)*	*SD*	*n*	*M (%)*	*SD*
Low	52.25	30.02	8	68.04	26.87	26	64.32	28.01
Adequate	79.30	11.97	30	79.42	17.37	33	79.40	14.92
High	82.55	12.31	22	85.17	9.53	18	83.73	11.09
Total	76.92	218.13	60	76.92	20.75	77	76.92	19.58

One-way ANOVA showed that the equal variance was violated. Kruskal-Wallis test was run and indicated that the difference was significant among the levels of attendance, p=0.006.

Post Hoc Games-Howell test showed that there was a significant difference between Low-level Attendance and Adequate Attendance in e-learning activities, (p=0.015), and between Low-level Attendance and High-level Attendance in e-learning activities, (p=0.001), in regard to students overall scores. In general, students who had adequate attendance in e-learning activities in both types of freshman classes performed significantly better than students who had low-level attendance in e-learning activities in both types of freshman classes; the mean difference in their overall final scores was 15.07 percentage points. The effect size was approximately equal to 0.70 (medium to large). Also, students who had high-level attendance in e-learning activities in both types of freshman classes performed significantly better than students who had low attendance in e-learning activities in both types of freshman classes; the mean difference in their overall final scores was 19.40 percentage points. The effect size was large (0.81).

Interestingly Games-Howell test showed that there was *not* a significant difference between Adequate Attendance and High-level Attendance in e-learning activities in regard to students' overall final scores, although there was a small mean difference (MD=4.33). This result demonstrated a non-linear relationship between the levels of attendance and students' overall performance scores.

Research Question 3. The third research question investigated whether there was a significant difference between students taking programming class, and students taking English-writing class, in regard to their end-of-term overall scores in blended-learning format.

Two-way Factorial ANOVA result showed that there was an insignificant difference between the freshman programming class and the freshman English-writing class in regard to students' overall scores; *t*-test supported the above conclusion.
Pre-planned ANOVA tests. The first pre-planned ANOVA test was to explore, for the applied-programming class alone, if there were statistically significant differences among students' levels of attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to their end-of-term overall scores in blended-learning format.

As illustrated in Table 4, one-way ANOVA showed that there was an overall significant difference among the levels of low, adequate, and high attendance in e-learning activities, F (2, 57) = 12.00, in regard to students' overall scores.

Since one-way ANOVA showed that the equal variance was violated, Kruskal-Wallis test was run and verified that the difference was significant among the levels of attendance, p=0.022.

Table 4
One-Way Analysis of Variance Summary Table Comparing
Levels of Attendance in Regard to Overall Scores in Applied Programming

Source	df	SS	MS	F	*p*
Overall Scores					
Between groups	2	0.574	.287	12.00	.00*
Within groups	57	1.364	.024		
Total	59	1.939			

*p<.05

Pre-planned Mann-Whitney U test showed that there was a significant difference between Low-level Attendance and Adequate Attendance in e-learning activities (p=0.020), and between Low-level Attendance and High-level Attendance in e-learning activities (p=0.010), in regard to students overall scores. In general, students who had adequate attendance in e-learning activities in applied programming class performed significantly better than students who had low-level attendance in e-learning activities; the mean difference in their overall scores was 27.12 percentage points. Also, students who had high-level attendance in e-learning activities in applied programming class performed significantly better than students who had low attendance in e-learning activities; the mean difference in their overall final scores was 30.30 percentage points.

Mann-Whitney U test showed that there was *not* a significant difference between Adequate Attendance and High-level Attendance in e-learning activities in regard to students' overall scores. This result again demonstrated a non-linear relationship between the levels of attendance and students' overall performance scores in applied programming class.

The second pre-planned ANOVA test was to explore, for the English-writing class alone, if there were statistically significant differences among students' levels of attendance in e-learning activities in regard to their end-of-term overall scores in blended-learning format.

As illustrated in Table 5, one-way ANOVA identified that there was an overall significant difference among the levels of low, adequate, and high attendance in e-learning activities, F (2, 74) = 4.41, in regard to students' overall scores. Since one-way ANOVA showed that the equal variance was violated, Kruskal-Wallis test was executed. Interestingly, the Kruskal-Wallis test resulted in an insignificant difference among the levels of attendance, p=0.092.

To further investigate the difference between low-level attendance and adequate attendance, between low-level attendance and high-level attendance, and between adequate attendance and high-level attendance in regard to students' end-of-term overall scores in English-writing class, pre-planned Mann-Whitney U tests were executed. The Mann-Whitney U test showed that there was an insignificant difference between Low-level Attendance and Adequate Attendance in e-learning activities (p=0.117), but there was a significant difference between Low-level Attendance and High-level Attendance in e-learning activities, (p=0.038), in regard to students overall scores. Although students who had adequate attendance in e-learning activities in the English-writing class performed better than students who had low-level attendance in e-learning activities, the mean difference in their overall final scores was 11.39 percentage points, which was not significant. However, students who had high-level attendance in e-learning activities in the English-writing class performed significantly better than students who had low-level attendance in e-learning activities; the mean difference in their overall scores was 17.13 percentage points.

Table 5
One-Way Analysis of Variance Summary Table Comparing
Levels of Attendance in Regard to Overall Scores in English-writing

Source	df	SS	MS	F	*p*
Overall Scores					
Between groups	2	0.348	.174	4.41	.016*
Within groups	74	2.925	.040		
Total	76	3.273			

*p<.05

Both *Post Hoc* Games-Howell and pre-planned Mann-Whitney U tests showed that there was *not* a significant difference between Adequate Attendance and High-level

Attendance in e-learning activities in regard to students' overall final scores; the mean difference was small.

Research Question 4. The fourth research question was to find out whether there was a significant correlation between virtual attendance in e-learning and students' end-of-term overall scores in blended-learning classes, and to further find out what the predictive model was to describe the effects of attendance on student performance.

Pearson correlation test was conducted to determine how well the e-learning attendance and students' end-of-term overall scores were correlated. Table 6 shows the means, standard deviations, and Pearson correlation coefficient between attendance and overall scores. Table 6 demonstrates that the variables are correlated well with each other.

Table 6 indicates that there was a significant correlation between the level of virtual attendance in e-learning activities and students' end-of-term overall scores, in both freshman programming and English-writing classes, $r\ (137) = .30$, $p < .001$. The direction of the correlation is positive, which statistically proves that students who have higher level of virtual attendance in e-learning activities earn higher end-of-term overall scores. Using Cohen's (1988) guidelines, the *r* indicates a medium to large effect size.

Table 6
Normalized Percent Means, Standard deviations, and Pearson correlation coefficient

Variable	M	SD	Attendance	Overall Scores
1. Attendance	38.08	20.74	--	.30**
2. Overall Scores	76.92	19.58	.30**	--

$^{**}p < .001$

As discussed in the previous parts of this paper, statistical results demonstrated a non-linear relationship between the levels of attendance and students' end-of-term overall performance scores. The non-linearity is illustrated in Figure 1.

The nonlinear characteristics shown in Figure 1 can be modeled by a set of piece-wise linear equations. Figure 2 further demonstrates the scatter-plot between the levels of attendance, in normalized time-scale, and students' end-of-term overall grades. Both Figure 1 and Figure 2 approximate a typical first-order dynamic system, which can be generalized by the following differential equation:

$$\tau \frac{dy}{dx} + y = C$$

In this specific research, y represents the end-of-term overall scores in terms of percentage, x represents student's attendance on a normalized time-scale, and C is a constant, representing the maximum value that y may potentially reach. Obviously, $C \cong 1$.

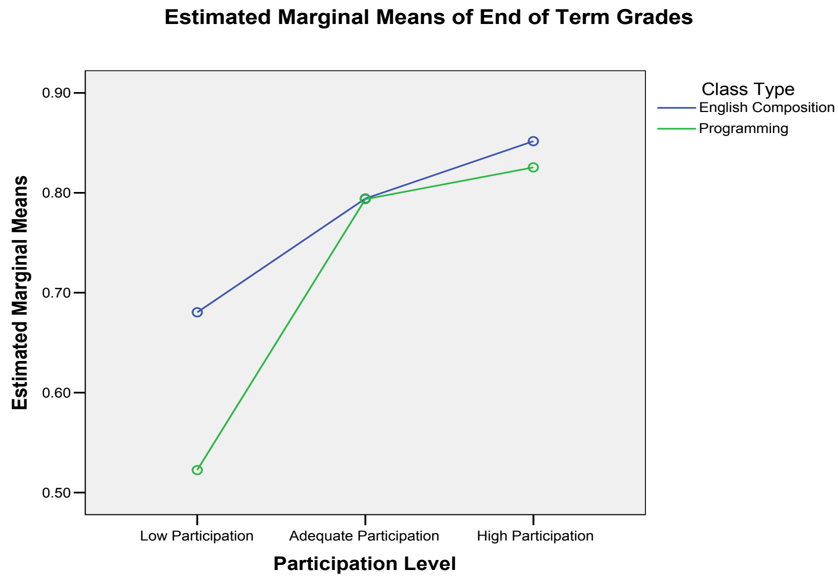

Figure 1. Non-linear Relationship Between the Levels of Attendance and Students' End-of-term Overall Performance Scores

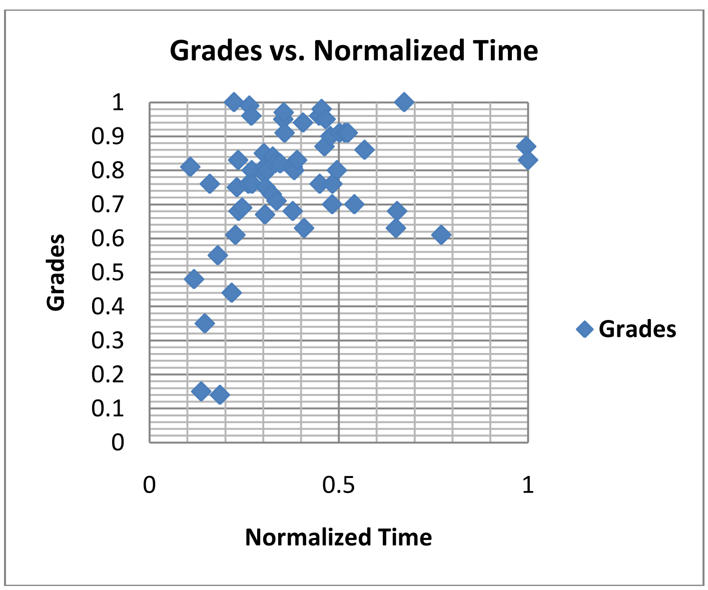

Figure 2. Scatter-plot Between the Levels of Attendance (Normalized) and Students' End-of-term Overall Grades

Using curve-fitting method, τ in the above equation was approximated as $\tau = 0.21$. Plug parameters into the above first-order differential equation:

$$0.21\frac{dy}{dx} + y = 1$$

Solving the above differential equation with an approximated horizontal shift on x-axis resulted in the following continuous exponential equation describing the relationship between the end-of-term overall scores versus the students' attendance on a normalized time-scale:

$$y(x) = 1 - e^{-\frac{x-0.09}{0.21}};\ for\ 0.09 < x < 1$$
$$y(x) = 0;\ for\ x < 0.09$$

The response curve of this predictive model simulated by the MATLAB is demonstrated in Figure 3. On the horizontal scale in Figure 3, 0-0.38 represents the range of low attendance; 0.39-0.55 approximates the range of adequate level attendance, etc. The vertical scale represents students' overall scores in terms of percentage.

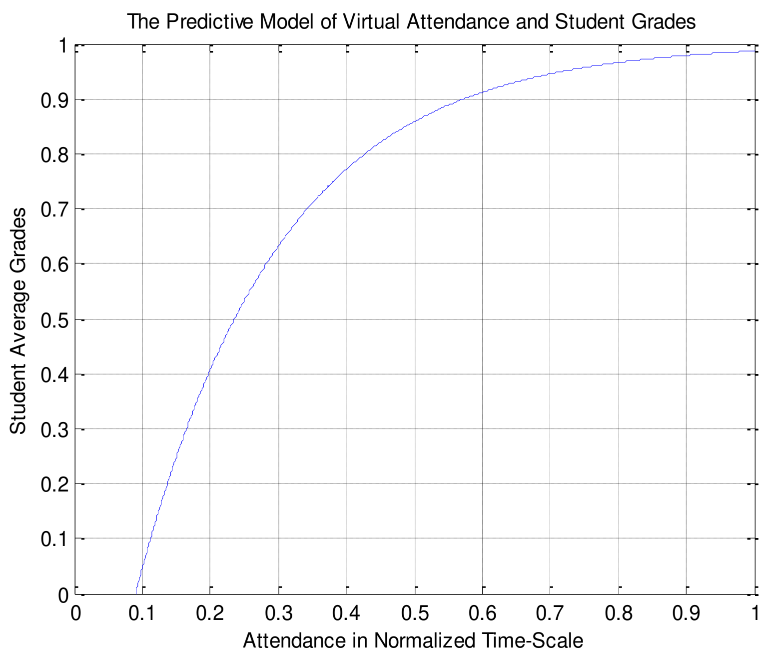

Figure 3. The Predictive Model between Virtual Attendance and Student End-of-term Overall Scores

Research Question 5. The fifth research question investigated the statistical differences among students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to the percentage of students

whose end-of-term overall scores were in the AB range, and in regard to the percentage of students whose end-of-term overall scores were in the DF range.
Figure 4 shows the differences among students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to the percentage of students whose end-of-term overall scores were in the AB range, and in regard to the percentage of students whose end-of-term overall scores were in the DF range. The solid line depicts the differences among students' levels of virtual attendance (low-level attendance, adequate attendance, and high-level attendance) in e-learning activities, in regard to the percentage of students whose end-of-term overall scores were in the AB range. The line demonstrates almost a linear relationship. The dotted line indicates the differences among students' levels of virtual attendance in regard to the percentage of students whose end-of-term overall scores were in the DF range. The line assimilates an exponential decay behavior.

Figure 4 illustrates that a majority of students obtained average grades of As or Bs, if their attendance had been better than adequate. On the other hand, DF rates increased sharply for students whose attendance was dropping below the adequate levels.

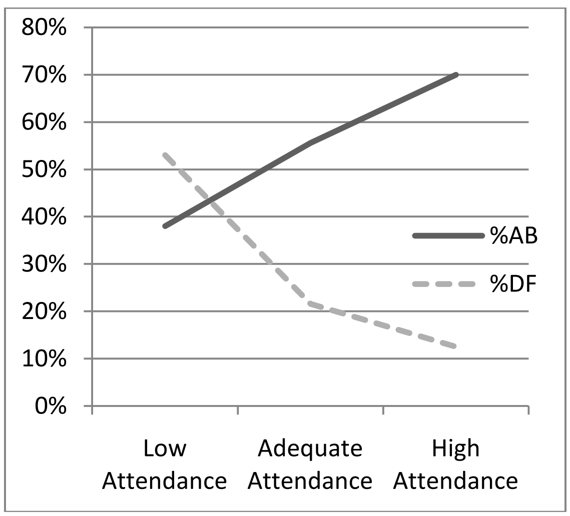

Figure 4. The Differences among Students' Levels of Virtual Attendance in Regard to the AB and DF Rates

Discussions

Significant differences among the levels of virtual attendance and students' overall performance. The research verified an overall significant difference among the levels of virtual attendance in e-learning activities in regard to students' overall scores. Students who had adequate or high-level virtual attendance in both programming and English-writing classes performed significantly better than students who had low-level virtual attendance in e-learning activities did. The research further verified that the relationship between the levels of virtual attendance and students' overall performance is non-linear.

Meanwhile, the study showed that there was no significant difference between students taking programming class and students taking English-writing class, in regard to their end-of-term overall scores in blended-learning format. This finding implied that for different types of classes, virtual attendance played an equally important role in achieving learning outcomes. Statistically speaking, the students taking blended-learning classes in different subjects performed equally well if their attendance in virtual components was equally adequate.

The correlation between virtual attendance in e-learning and students' end-of-term overall scores in blended-learning classes. The research proved a significant correlation between the level of virtual attendance in e-learning activities and students' end-of-term overall scores. Students who had higher level of virtual attendance in e-learning activities earned higher end-of-term overall scores. The results in this research indicated that simple measures such as virtual attendance data provided strong predictions of students' overall grades in blended learning classes. The results are not astounding, as referenced to the previous research findings on the effect of face-to-face classroom attendance on students' end-of-term academic performance (Douglas, 2008). The results supported the general conclusion made in earlier studies for on-site, face-to-face learning scenarios, that attendance, both in classroom and virtually, is strongly correlated with students' performance and their GPAs (Crede et at., 2010).

The model derived in this research may serve as a useful instrument to predict student performance based on their virtual attendance in blended-learning components. It can be used as an advising tool for the newly implemented student central structure at many universities. As Moore et al. (2003) demonstrated, emphasizing the critical nature of attendance to students at the starting of an academic term could improve students' end-of-term average scores by 9% as compared to a similar course where the importance of attendance was not emphasized (Moore et al., 2003, as cited in Crede et al., 2010). This predictive model can be presented at New Student Orientation sessions, and at the beginning of each academic term as a rhetorical reminder of the importance of attendance. During the academic terms, the model can help to trigger attendance warnings for students who showed early signs of low attendance, so that student academic advisors may contact these students to identify and resolve the potential issues that keep students from persisting in learning.

This research again proved the findings that that the actual effect of attendance on student performance was not linear (Durden and Ellis, 1995). The nonlinear characteristic is modeled by a first-order dynamic system. On the one hand, the nonlinearity implies that almost all students must attend adequately in order to earn decent grades; on the other hand, the expectation for the "adequacy" of attendance, especially for virtual attendance where students and professors are not face-to-face, should be clearly transparent. The nonlinearity indicates that abundant over-attendance may not result in the highest outcome. To realize the optimum point of learning efficiency on a learning-curve in terms of an ideal combination of time versus grades is critical for all learners in the blended-learning world.

Experiences suggest that if students are aware of their attendance early enough as compared to professor's expectation for adequate attendance and to their peers in the same classes during the term, they would be willing to invest more effort and time and to increase their participation to obtain higher grades (Douglas, 2008). With the continuous success of the early-intervention process across higher learning institutions, the virtual attendance data across all courses for each student should be incorporated into an automated attendance data-base, which allows student academic advisors to quickly receive the real-time identification for students whose attendance falls below the adequate level. This information will facilitate academic advisors, professors, and academic administrators to offer immediate remedial assistance and take proactive actions. With the transition to blended-learning methodology, students may need additional advisement in adjusting their learning habits, especially if they are first-year freshman students (Douglas, 2008).

Significant differences among students' levels of virtual attendance in regard to students' AB and DF rates. The research identified that a majority of students obtained As or Bs if their attendance had been better than adequate; and a large percentage of DF students' virtual attendance were in the range of lower levels.

For the sample in this study, 53% of students who had low-level virtual attendance would end up with DF grades, which resulted in approximately 12.2% of total student population who obtained DFs. Figure 5 depicts the relationship between the improvement of virtual attendance (reduction in the percentage of students who have low-level virtual attendance), and the reduction in students' DF rates.

Based on the above predictive curve, with proactive early intervention, if the percentage of students with low-level virtual attendance were to reduce from 23% to 11% (50% improvement), the DF rate would be reduced by more than 50% (from above 12% to under 6%). This calculation verified the conclusion that stressing the importance of attendance to students would substantially reduce the failure rate (Crede et al., 2010), which would eventually improve student learning persistence.

Limitations. In traditional face-to-face teaching, classroom attendance is one of the most accepted measures of participation (Douglas, 2008). As Douglas (2008) discussed, all measures of attendance were "crude" as they only provided information regarding physical presence, rather than learners' cognitive participation. For blended-learning or online learning, a student might bruise through virtual components but not try to comprehend them (Douglas, 2008).

Although this research proved that virtual attendance strongly correlated to student academic performance, the level of virtual "presence" in e-learning activities does not necessarily reflect the actual level of active participation. For blended-learning or online learning delivery formats, how to define attendance or participation is controversial. Due to a lack of qualitative assessment with the existing virtual attendance tracking tools, what is considered as "adequate participation" and how to continue to create technologies to measure e-learning participation in a reliable and valid way remain as further research topics (Douglas, 2008).

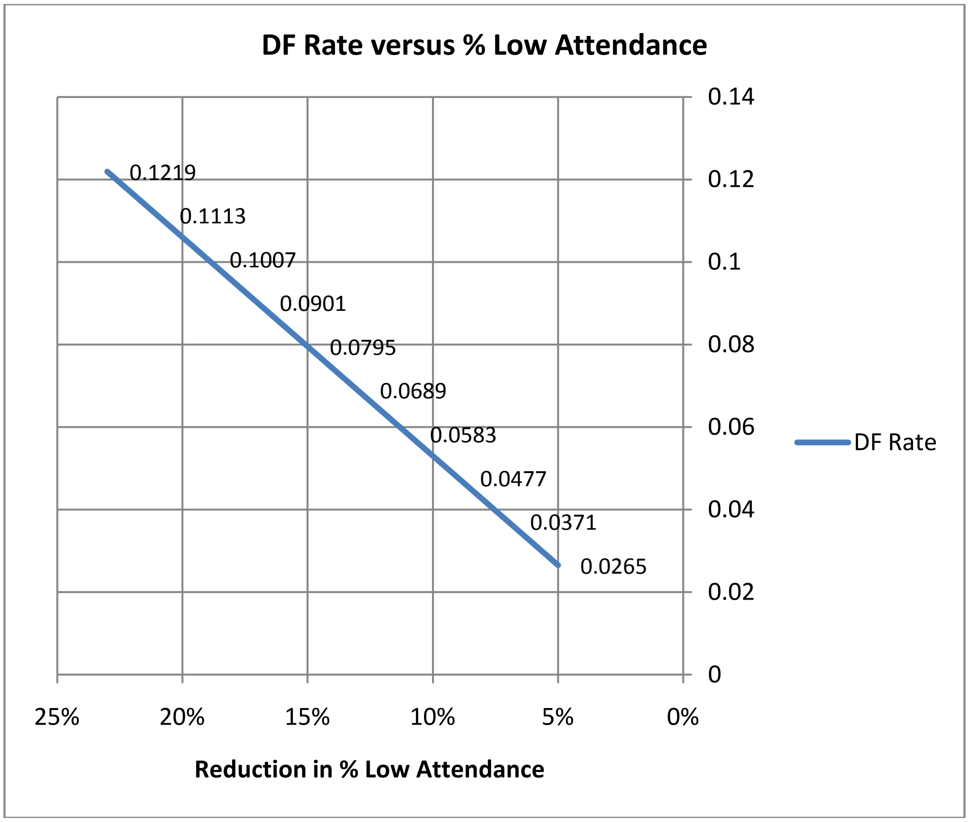

Figure 5. The Relationship between the Improvement of Virtual Attendance and the Reduction in Students' DF Rates

Conclusion

The research revealed that students who had better virtual attendance in e-learning activities performed significantly better than student who had low-level virtual attendance, in regard to end-of-term overall scores, in blended-learning format in both applied-programming class and English-writing class. The research also found a significant correlation between the level of virtual attendance in e-learning activities and students' end-of-term overall scores, in both types of classes. The research suggested that the positive attendance-performance relationship was similar regardless the types of subjectmatters. The research indicated that students' level of virtual attendance strongly predicted their overall grades in blended learning classes.

The research supported the meta-analytical findings that the critical role of attendance has not significantly changed over time; and therefore the increased adaptation of online learning components has not reversely reduce the importance of attendance (Crede et al., 2010).

The predictive model can be used as an advising tool for student academic advisors to approach the students who showed early signs of low virtual attendance to potentially identify the issues and resolutions to the issues, in order to help these students persist in blended-learning. The research provided evidence that improved virtual attendance will substantially reduce the DF rates and eventually improve persistence.

The key significance of this research is the reiteration of the learning theories that stress the ultimate importance of attendance, so that the increased contacts with professors, repeated reviews of instructional contents, and on-time completion of exercises would occur (Crede et al., 2010).

Another critical significance of this research, due to the effective prediction of students' success based on their level of attendance, is for students themselves, student academic advisors, student finance advisors, professors, and academic administrators, to closely monitor all students' onsite and virtual attendance records in blended-learning classes. Even a small improvement may contribute a piece of benefit that accrues progressively. Reducing every single failure in every single class can speed up student's degree-completion by a time increment, resulting in a reduction in student tuition and fees, improving the time-to-degree cycles, help student's entrance into the labor market faster, and substantially increase student's life-time earnings (Crede et al., 2010).

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