Effect of Geographic Distance on Distance Education: An Empirical Study

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Abstract

This study investigates the effect of geographic distance on students' distance learning experience with the aim to provide tentative answers to a fundamental question – does geographic distance matter in distance education? Using educational outcome data collected from an online master's program in Geographic Information Systems, this study calculates the distance between students' residences and the program location, and employs three hierarchical multiple regression models to examine how well geographic distance can predict a student's online learning performance, satisfaction with the program, and length of time to complete, when controlling for other relevant factors. Our research findings provide empirical evidence to support the claim that the development of information and communication technologies (ICTs) has in fact overcome the potential barriers that may be associated with distance in education and has provided an effective bridge between students and educational programs. The study also reveals interesting discoveries regarding the relationship between students' distance learning experience and certain student characteristics such as age, gender, and previous academic achievement.

Keywords: distance education, online learning, geographic distance, prediction model

INTRODUCTION

Distance education, as defined by Moore and Kearsley (2011), is teaching and planned learning in separate spaces that require communication through technologies and special institutional organizations. The communication technologies for distance education have evolved from paper-based correspondence to electronic delivery mechanisms such as television broadcasting, video conferencing, online learning management systems, and mobile applications. Consequently, the geographic distance covered by distance education programs has expanded from adjacent towns and cities to remote countries and continents (Beldarrain, 2006; Zhang & Kenny, 2010). Today, distance education constitutes a critical part of the U.S. higher education system as there is a significant and growing number of college courses and degree programs offered online to geographically-dispersed students around the world (Allen & Seaman, 2011; Moore & Anderson, 2012). Due to the web-based nature of distance education today, the authors will use the term *distance education* interchangeably with the terms *online instruction* and *online education* in this study.

The rapid advancement of information and communication technologies (ICTs) such as the Internet has greatly reduced the time and cost of transporting data and ideas (Cairncross, 2001). Thus, it is a logical expectation that these technologies will bridge the gap of geographic distance that separates learners from institutions, instructors, and each other (Andrews & Haythornthwaite, 2007; Beldarrain, 2006; Moore, 2007). However, this expectation has yet to be verified, as there is a lack of empirical studies that evaluate the effects of geographic distance on students' distance learning experience. As a result, it is still difficult to provide answers confidently to a fundamental question for distance education – does geographic distance matter in distance education?

To address such a need in distance education research, this study investigates the effect of geographic distance on students' learning experience in an online master's degree program in Geographic Information Systems (MGIS). The MGIS program is offered by the Pennsylvania State University (PSU), a large public research university in the northeastern region of the United States. From the program's inception in 2005 to the summer of 2013, the total cumulative enrollment was 362 students from 48 states and 4 countries (Figure 1). The MGIS program has been populated by adult working professionals with an average age of 40, who typically complete one course at a time in 10-week class sessions. By calculating the distance between students' residences and the program location and examining its effects on different aspects of online learning, this study aims to determine if geographic distance should be considered as a significant factor for distance education. More specifically, this study tests the following three hypotheses:

- Hypothesis 1: Geographic distance is a significant predictor for a student's graded performance in the distance education program.
- Hypothesis 2: Geographic distance is a significant predictor for a student's satisfaction with the distance education program.
- Hypothesis 3: Geographic distance is a significant predictor for the total time a student takes to complete the distance education program.

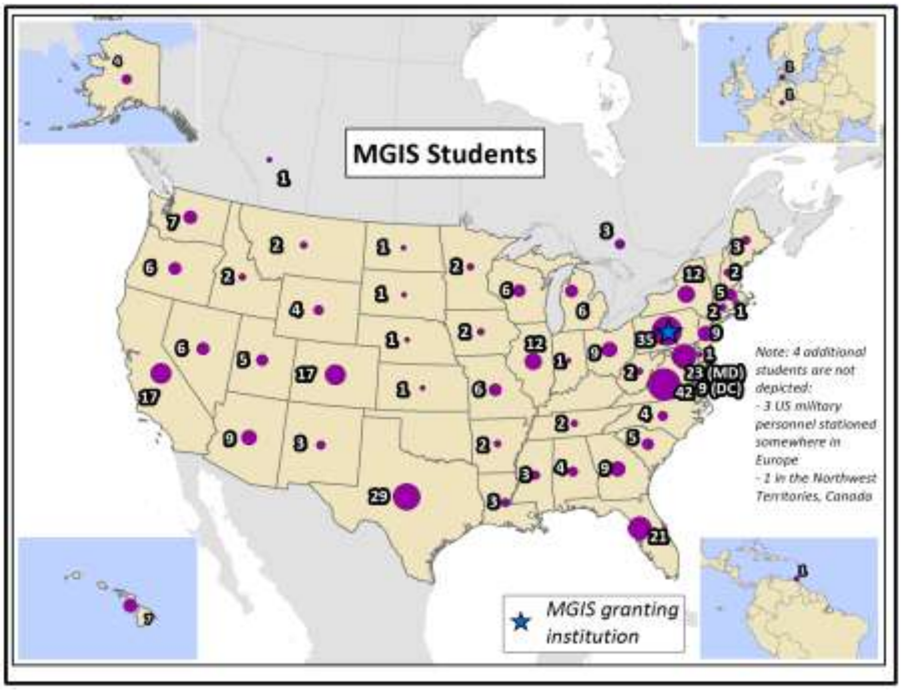

Figure 1. Geographic distribution of students in the MGIS program

REVIEW OF THE LITERATURE

In order to examine the unique effects of geographic distance on the MGIS distance education program, it is important to first identify the other relevant factors and control for their effects on students' online learning experience. The literature commonly classified the factors influencing distance education into two major categories: student variables (e.g., age, gender, previous academic achievement, prior experiences) and course/program variables (e.g., pedagogical features, level of interaction and collaboration, resources and support). Because all participants in this study were enrolled in the same online program (MGIS) with the same or highly similar course/program variables, the authors expected that most variance in participants' online learning experience should be attributed to the student variables. As a result, the review of literature in this study focused on examining a list of student variables and their effects on three aspects of distance education: learning performance, learner satisfaction, and completion rate.

Age

Many researchers have examined the influence of age on students' online learning experience and reported mixed findings. While some studies found age to be a significant predictor of students' online learning performance (Fredericksen et al., 2000; Lim & Morris, 2009) and program retention rate (Pierrakeas et al., 2004), other studies reported no significant correlations between age and those two variables (Cheung & Kan, 2002; Hong, 2002; Levy 2007; Martínez-Caro, 2011; Osborn, 2001; Yukselturk & Bulut, 2007; Willging & Johnson, 2004). In terms of learner satisfaction, most empirical evidence suggests that age has no real effect on how students perceive their learning experience in the online programs (Arbaugh, 2001; Hong, 2002; Yukselturk & Bulut, 2007).

Gender

In the early days of online instruction, many researchers considered women to be disadvantaged based on the assumptions that women lack the computing skills and personal interest to study online (Anderson, 1997; Blum, 1999; McSporran & Young, 2001; Spender, 1995). However, such assumptions turned out to be inaccurate as the empirical evidence indicates that gender has no significant impact on students' online learning performance (Arbaugh, 2001; Hong, 2002; Lim & Morris, 2009; Martínez-Caro, 2011; Yukselturk & Bulut, 2007), and that gender cannot predict whether a student will successfully complete an online program (Kemp, 2002; Pierraskeas & Xenos, 2004; Tello 2007; Xenos et al. 2002). In fact, several studies have reported opposite evidence, showing female students tend to enjoy their online learning experience more than their male counterparts and report higher perceived satisfaction with the online learning programs (González-Gómez et al., 2012, Sanders & Morrison-Shetlar, 2001; Swan et al., 2001).

Prior Online Learning Experience

Students' prior experience with online instruction is found to have significant effects on their current distance education experience: Students who had online courses before tend to be more competent at managing their online learning process thus outperform their peers who are new to online instruction (Alavi et al., 2002; King et al., 2000; Lee at al., 2001; Marks, Sibley, & Arbaugh, 2005). Several studies have also identified prior online learning experience as an indicator for discriminating completing and non-completing students in distance education programs (Cheung & Kan, 2002, Dupin-Bryant, 2004). Moreover, Arbaugh (2008) finds that prior online learning experience is one of the strongest predictors of learner satisfaction. Several other studies support this finding, showing experienced online learners are more likely to rate their online programs as preferable or satisfying (Artino, 2007; Lim & Morris, 2009; Martínez-Caro, 2011).

Self-Regulation

Self-regulation skills (e.g., goal-setting, strategy selection, planning, and self-monitoring) prepare students for the self-directed nature of online learning environment and enable them to manage their online learning process more effectively (Zimmerman, 2008). Empirical evidence indicates that students with more developed self-regulation skills are more likely to achieve better learning outcomes in online courses (King et al., 2000; Puzziferro, 2008; Yukselturk and Bulut, 2007). Furthermore, several studies have shown that students' level of satisfaction with their online learning programs and the likelihood they will complete are also significantly related with their self-regulation measurement (Artino, 2007; Morris et al., 2005; Parker, 2003; Puzziferro, 2008).

Previous Academic Achievement

Many empirical studies have proven previous academic achievement to be one of the leading predictors for students' college performance. For example, high school grade-point average (GPA) has been an important criterion for most university and college admissions, and Wolfe and Johnson (1995) also found in their study that 19% of the variance in college GPA can be predicted by high school GPA. Previous academic achievement is also found to be positively correlated with college students' performance online (Alstete & Buetell, 2004; Cheung & Kan, 2002; Diaz, 2002), and students with good academic records are more likely to successfully complete their online courses or programs (Cheung & Kan, 2002; Dupin-Bryant, 2004; Morris et al., 2005). However, there seems to be few empirical studies that examine the relationship between students' previous academic achievement and their level of satisfaction with the online learning programs.

In summary, our literature review has identified five student variables that were widely researched in the literature and has examined their influence on different aspects of distance education. These findings are summarized in Table 1.

Table 1
Student Variables Influencing the Effectiveness of Distance Education

	Learning Performance	Learner Satisfaction	Completion Rate
Age	Inconclusive: significant in some studies (Fredericksen et al., 2000; Lim & Morris, 2009) but not others (Martínez-Caro, 2011; Yukselturk & Bulut, 2007).	Insignificant (Arbaugh, 2001; Hong, 2002; Yukselturk & Bulut, 2007).	Inconclusive: significant in some studies (Pierrakeas et al. 2004) but not others (Osborn, 2001; Levy 2007; Willging and Johnson, 2004).
Gender	Insignificant (Arbaugh, 2000; Lim & Morris, 2009; Martínez-Caro, 2011; Yukselturk & Bulut, 2009)	Significant (González-Gómez et al., 2012, Sanders & Morrison-Shetlar, 2001; Swan et al., 2001)	Insignificant (Kemp 2002; Tello 2007; Xenos et al. 2002)
Prior online learning experience	Significant (Alavi et al., 2002; Arbaugh, 2008; King et al., 2000; Lee et al., 2001)	Significant (Lim & Morris, 2009; Martínez-Caro, 2011)	Significant (Cheung & Kan, 2002; Dupin-Bryant 2004)
Self-regulation	Significant (King et al., 2000; Yukselturk & Bulut, 2007)	Significant (Artino, 2007; Puzziferro, 2008)	Significant (Morris et al., 2005; Parker, 2003)
Previous academic achievement	Significant (Alstete & Beutell, 2004; Diaz, 2002)	Not reported	Significant (Cheung & Kan, 2002; Dupin-Bryant 2004; Morris et al., 2005)

Theoretical Framework

Based on the review of literature and the characteristics of the MGIS program, this study has identified a list of possible variables that can predict MGIS students' online learning experience. Our classification and understanding of the relationship between those variables are illustrated in the theoretical model shown in Figure 2. According to this model, the combination of four student variables and two distance variables is able to predict three important aspects of distance education: learning performance, learner satisfaction, and completion time.

Most students enrolled in the MGIS program have already completed an online GIS certificate program offered by PSU, and this is the recommended progression as stated by the MGIS program. As a result, the authors considered *prior online learning experience* to be a ubiquitous attribute for the students, and thus excluded this student variable from the theoretical model that predicts students' online learning experience. The other four student variables (*age*, *gender*, *self-regulation* and *previous academic achievement*) differ among individual students therefore are included in the model as the possible predictors.

Because all students in this study have attended the same MGIS program offered by the same university, program variables such as subject domain, pedagogical design, and resources are expected to affect all students in the same way. As a result, the authors believe program variables in this study do not contribute to the variance of students' online learning experience, and thus excluded them from the theoretical model. Several students also mentioned in their exit interview after graduation from the MGIS program that there was an impact from time zone differences on their online learning activities such as assignment submission or group collaboration. As a result, this study examined both *time zone difference* and *geographical distance* as distance variables.

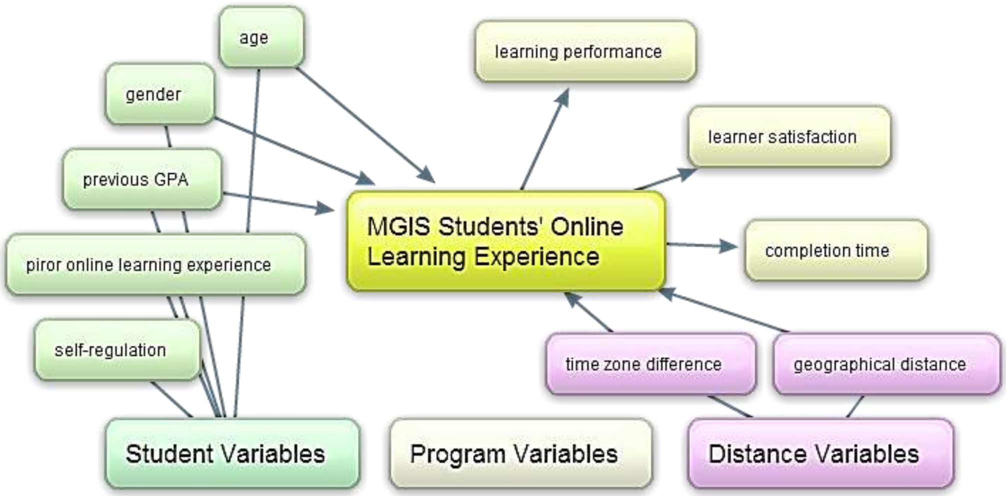

Figure 2. The theoretical model for predicting MGIS students' online learning experience

METHODS

Data Source

The primary data source for this study is a student database managed by the MGIS program that stores students' demographic information, registrar records, and evaluation documentation. A total number of 362 student records were collected from the database, with 194 students who are currently enrolled in the MGIS program and 168 students who have already graduated. Students' demographic information (e.g. age, gender) and their junior/senior year GPAs were obtained from their application forms, which had been scanned and stored in the database. The course grades, cumulative GPAs, and program start and end dates for the MGIS students were retrieved from the registrar records. Students' self-reported addresses are also part of their registrar records, which were used to calculate the geographic distance and time zone differences between student residences and the main campus of PSU that offers the MGIS program.

There are also two relevant types of evaluation documents stored in the database: subjective evaluation ratings of student performance by program faculty during their coursework and the transcripts of students' exit interviews after graduation. The subjective evaluations represent instructors' assessment of how well a student managed the online learning tasks and the extent to which the student reached his or her full potential to succeed, which provides a good indication of a student's self-regulatory skills. The evaluation from each instructor consists of a numeric rating and a written comment. This study uses the average of these numeric ratings from all faculty as a measure of self-regulation for students.

The MGIS faculty would conduct an exit interview with each MGIS student when he or she graduated, in which the student would describe the overall learning experience with the MGIS program and comment on its usefulness, strengths and weaknesses. As a result, this study coded the interview transcripts to provide a measure of learner satisfaction with the MGIS program. The guidelines and examples for coding learner satisfaction from students' exit interviews are described in Table 2.

Table 2
The Guidelines and Examples for Coding Learner Satisfaction

Code	Guideline for Coding	Example of Coding
3 very satisfied	The student's comments regarding the program are highly positive without mentioning any major problems or weaknesses, and the student would strongly recommend the program to others	"I would recommend the program to anyone. It was great. I would not have considered getting my masters if it weren't for your program. It was fabulous for me."
2 somewhat satisfied	The student expresses his or her preference for the program but also points out a few weaknesses of the program or one or two problematic courses.	"That (the program) has really worked for me...seemed like instructor was overwhelmed a bit in (course name) - feedback not timely enough…I don't like working in teams..."

Code	Guideline for Coding	Example of Coding
1 not satisfied	The student is not sure if the program is worthwhile of their time and money and clearly states his or her frustration over many issues in the program	"For me, it (the program) didn't really help me in my job. Professionally, I'm not seeing the pay-off. Would I do it again? I don't know. It is a lot of money."

To summarize, Table 3 lists all the variables examined in this study and explains how each variable was operated by describing its indicators, data source and measurement.

Table 3

Operational Variables in This Study and Their Indicators, Data Sources, and Measurement

Variable	indicators	Source	Measurement
Age (age)	number of years	application form	25-70 (year)
Gender (gender)	male or female	application form	1 (F), 0 (M)
Self-regulation (self_reg)	faculty ratings and evaluation comments	faculty's subjective evaluation	0-4 (0:low; 1:below average; 2:average; 3: above average; 4: exceptional)
Previous GPA (gpa_pre)	junior/senior year GPA	application form	1.9-4.0 (grade-point average)
Geographical distance (dist)	calculated distance between student self-reported address and the MGIS location	registrar records	1-4740 (mile)
Time zone difference (time_diff)	number of time zones between locations	registrar records	0-6 (hour)
Graded learning performance (gpa)	student GPA for the MGIS program	registrar record	2.64-4.0 (grade-point average)
Learner satisfaction (satisf)	student comments about their learning experience in the program	exit interview transcript	1-3 (1: not satisfied; 2: somewhat satisfied; 3: very satisfied)
Completion time (comp_time)	number of terms (10-week) between program start and end dates	registrar records	6-45 (terms)a

[a] The program operated on four 10-week terms from 2005 – 2011 and now operates on five 10-week terms beginning Spring 2012.

Hierarchical Multiple Regression Analysis

This study employs hierarchical multiple regression to calculate how much variance in students' online learning experience with the MGIS program can be predicted by the distance variables, when controlling for effects of the student variables. Hierarchical multiple regression is a flexible data-analytic method to explain or predict an outcome (dependent) variable with a set of predictor (independent) variables. It has been commonly used in the literature to test theory-based hypotheses regarding the effect of a specific predictor and examine how much the predictor adds to the prediction of an outcome variable (Cohen, 2001; Cohen, Cohen, West, & Aiken, 2003).

Three multiple regression models have been established in this study to test the three hypotheses on the effects of geographic distance. Based on the theoretical model shown in Figure 2, this study entered the four student variables (*age*, *gender*, *self-regulation, previous GPA*) and the two distance variables (*geographical distance* and *time zone difference*) sequentially into the regression models as the predictor variables, and selected the three aspects of distance education (*online learning performance*, *learner satisfaction*, and *completion time*) as the outcome variables. By determining if the two distance variables contribute significantly to the variance in MGIS students' online learning performance, learner satisfaction, and completion time, the authors can make the decisions to accept or reject the three hypotheses.

It is important to note that the data for some variables are missing for certain groups of students. For example, *completion time* is only applicable for graduated students, and *learner satisfaction* can only be coded and assigned to the students who have participated in the exit interview. Participants with missing data were excluded listwise from the regression models during the data analysis. This study selected SPSS (ver. 21.0) as the statistical analysis package to run regression analyses.

RESULTS

Table 4 lists the inter-correlations among predictor variables and outcome variables. As expected, the variable *geographical distance* is highly correlated with the variable *time zone difference* ($r=.954$, $p<.001$). To avoid the problem of multicollinearity, *time zone difference* was excluded from the regression models. *Geographical distance* is also correlated with *gender* at a significant level ($r=.127$, $p<.05$), indicating more women than men tend to take the MGIS program at greater distance. *Age* is significantly correlated with completion time ($r=.298$, $p<.01$), showing that older students generally took more time than did younger students to finish the MGIS program. Consistent with previous research findings, students' *self-regulation* is found to be significantly correlated with their *online learning performance* in the program ($r=.434$, $p<.01$). It is interesting to note the negative correlation between students' *online learning performance* and *completion time*, which suggests that students on the fast track actually got higher grades in their courses. Contradictory to what the literature suggests, *previous GPA* in this study has no significant correlation with other variables such as *self-regulation*, *online learning performance*, and *completion time*.

Table 4

Inter-Correlation between Predictor Variables and Outcome Variables

	dist	time_diff	age	gender	self_reg	gpa_pre	gpa	satisf	comp_time
dist	-	.954**	.019	.127*	.042	-.027	.022	-.080	.075
time_diff		-	.014	.098	.050	-.018	.060	-.088	.107
age			-	.039	.059	-.022	-.049	-.019	.298**
gender				-	-.020	.037	-.076	-.090	.097
self_reg					-	.038	.434**	-.163	.028
gpa_pre						-	.056	-.166	-.090
gpa							-	-.029	-.163*
satisf								-	-.116
comp_time									-

*p<.05; **p<.01

Hypothesis 1-Rejected

This study developed a hierarchical multiple regression model to test Hypothesis 1, with student variables added to the regression model in the first step and *geographical distance* added in the second step. Table 5 summarizes the key statistical results. As shown in Table 5, student variables in combination can significantly predict students' online learning performance, accounting for about 19.5% of total variance in their GPAs. However, *self-regulation* turns out to be the only significant predictor (β =.43, p<.01). *Geographical distance* is not a significant predictor for GPA (p=.587 >.05), and the addition of *geographical distance* in the regression model does not increase the total variance that can be predicted. In other words, geographic distance does not have a significant impact on students' online learning performance, and Hypothesis 1 should be rejected.

Table 5

Regression Model Summary for Predicting Online Learning Performance (gpa) (N=360)

Predictor	B	β	sig	R^2	ΔR^2
Step1: student variables (age, gender, self-reg, gpa_pre)				.195**	.195
Step 2: student variables and distance				.196**	.001
age	-.002	-.091	.099		
gender	-.011	-.030	.585		
self_reg	.177**	.430**	.000		
gpa_pre	.021	.051	.353		
dist	5.751E-006	.030	.587		
constant	3.460		.000		

*p<.05; **p<.01

Hypothesis 2 – Rejected

Table 6 summarizes the key statistical results from the regression model that uses student variables and *geographical distance* to predict student satisfaction. The predictors in combination contribute only 4.7% of the total variance in student satisfaction, and none of the predictors in the model are statistically significant. The variable *geographical distance* adds little predicting capacity to the regression model (ΔR^2=.003) As a result, this study concluded that geographic distance has no impact on students' general satisfaction towards the distance education program, and therefore Hypothesis 2 should be rejected.

Table 6

Regression Model Summary for Predicting Student Satisfaction (satisf) (N=103)

Predictor	B	β	sig	R^2	ΔR^2
Step1: student variables				.044	.044
(age, gender, self-reg, gpa_pre)					
Step 2:student variables and distance				.047	.003
age	.002	.030	.787		
gender	-.102	-.097	.388		
self_reg	-.092	-.065	.562		
gpa_pre	-.187	-.153	.172		
dist	-3.377E-005	-.058	.598		
constant	3.528		.000		

*p<.05; **p<.01

Hypothesis 3-Rejected

Table 7 presents the regression model that predicts the amount of time students take to finish the MGIS program. The combination of student variables can predict 13% of the total variance in students' completion time, but age is the only significant predictor (β=.305, p<.01) among the student variables. The regression model also shows that *geographical distance* cannot predict students' completion time, and the inclusion of this variable in the regression model contributes little to its overall prediction capacity (ΔR2=.003). In other words, geographic distance does not affect how long a student takes to complete the distance education program, and thus Hypothesis 3 should be rejected.

Table 7

Regression Model Summary for Predicting Program Completion Time (comp_time) (N=162)

Predictor	B	β	sig	R2	Δ R2
Step1: student variables				.130**	.130
(age, gender, self-reg, gpa_pre)					
Step 2: student variables and distance				.133**	.003
age	.221**	.305**	.001		
gender	1.475	.111	.201		
self_reg	-1.225	-.071	.409		
gpa_pre	-1.395	-.095	.257		
dist	.000	.052	.543		
constant	3.528		.019		

*p<.05; **p<.01

CONCLUSION AND DISCUSSION

This study contributes to the literature by providing tentative answers to a fundamental question – does geographic distance matter in distance education? The rejection of the three research hypotheses suggests that geographic distance does not matter since it has no significant impact on students' online learning performance, satisfaction, and the length of time to complete the program. The results are not surprising given the fact that the MGIS program relies primarily on asynchronous communication and all course content is delivered instantaneously through the Internet. Informal qualitative feedback from students located far away from the university has also consistently revealed strong affinity for the program and university, despite what one may expect given the fact that many students never visit campus physically. The statistical results from our study provide empirical evidence to support the claim that the development of ICTs has in fact overcome the potential barriers that may be associated with distance in education, when the distance education programs are primarily implemented asynchronously. However, it is reasonable to expect that geographic distance and time zone difference might have a greater effect in programs with a significant synchronous component. In addition, since this study was conducted in the context of a graduate degree program in geography, we recognize that its findings may not be generalizable to other distance educational contexts such as undergraduate programs in humanities or social science.

This study also revealed several interesting discoveries that are worth further investigation. The first discovery is that students' junior and senior year undergraduate GPAs cannot predict their performance in the MGIS program. This phenomenon might be due to the small variance in both the predictor variable (gpa_pre, σ=.43) and the outcome variable (gpa, σ=.18), as students who enrolled in the master's program are very similar in terms of academic background and aptitude, and grades for graduate level courses tend to be inflated with most of the students earning an A or A- (Jewell, McPherson, & Tieslau, 2013). Another explanation is that the majority of the participants are adult learners who graduated from their undergraduate institutions a long time ago, and their college GPAs no longer accurately reflect their learning aptitudes. About 69% of the MGIS students were aged 35 or older at the time of the study, which means that in most cases at least a decade has passed since they earned their bachelor's degrees. As a result, maturity, motivation, and professional experience might be better predictors of MGIS students' academic performance than their college GPAs 10 or more years ago.

Another discovery is that gender is positively correlated with distance, which seems to suggest that more women are willing to take this program at a greater distance than their male counterparts. A further examination of the students' demographic information reveals that a sizable proportion of MGIS students (N=77) come from the adjacent Washington D.C. metropolitan area (Maryland, Northern Virginia, and Washington D.C.) , which in our sample skews more towards male (74%) than the rest of the student population (64%), possibly due to the fact that more men than women are involved in national security disciplines in the D.C. area, and learning about GIS is currently highly relevant to people working in this domain. If all D.C. area students are excluded from the analysis, then gender is no longer significantly correlated with distance (r=.109, p=.065 >.05, N=285). In other words, there is no difference between men and women in their willingness to study at a distance.

Further investigation is needed to determine the extent to which age affects students' online completion rates and completion times, as age appears to have little effect on students' performance and attitude. If older students are satisfied with the distance education program and are doing well academically, then there must be other factors behind their prolonged completion time. One factor might be workload: we believe that older students in the MGIS program are more often in leadership positions within their organizations and therefore may have less time available to dedicate to their distance education. Another possible factor is motivation: Older students are usually more established in their careers, and therefore may not feel as much immediate pressure as younger students to obtain a Master's degree for career-development reasons.

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