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When Size Does Matter: Identifying Multilevel Factors Contributing to IT Major Choice

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ABSTRACT

The current enrollment crisis in information technology (IT) has left employers scrambling to find qualified individuals to fill positions in IT within the corporation. One issue facilitating this dearth of workers is the lack of individuals pursuing IT-related majors. This research uses high school students to investigate the reasons behind individual choice to major in IT. Social Cognitive Career Theory (SCCT) is used as a theoretical framework for better understanding these decisions and group-level contextual supports/barriers are investigated in a multilevel context. Findings show strong support for school size as a significant school-level predictor of intention to major in IT and as a moderating influence on the effect of interest on intent to major.

Keywords

social cognitive career theory, career choice, multilevel modeling, group differences, school size, enrollment

INTRODUCTION

The recent state of Information Technology (IT) college enrollment both in the US and abroad paints a sad portrait for the discipline with stagnant or declining enrollments leading to a supply problem for entry-level talent (Akbulut-Bailey 2012; Benamati et al. 2013; Looney et al. 2014). This comes at a time when growth within the industry is expected to continue through 2024 at a rate of over 15 percent (BLS 2014). Even after accounting for the current dismal economic environment, the need for trained IT professionals is currently quite high. If not addressed, this deficiency in needed talent could negatively affect corporate environments and jeopardize IT departments currently present in universities.

Social Cognitive Career Theory (SCCT) has been used extensively within counseling and career psychology as a method for understanding how individuals develop vocational interests, make occupational choices, and achieve success within their chosen field (Lent 2005). The base model has been utilized in IS (Heinze et al. 2009), including investigating the role of contextual supports/barriers (Akbulut-Bailey 2012; Akbulut-Bailey 2011; Akbulut et al. 2009), but this research has all been at the individual level of analysis. No research has looked at the effects of group-level contextual supports/barriers on individual choice to major.

The purpose of this paper is to examine group-level contextual support/barrier effects on individual intent to major in IT within the context of the SCCT model. Specifically, we will analyze how school size impacts the intention to major of high school students across 40 different high schools. Our hope is to spur greater investigation of these group-level effects to gain a better picture of the college major choice process and improve enrollment numbers.

SOCIAL COGNITIVE CAREER THEORY

Social cognitive career theory (SCCT) (Lent 2005; Lent et al. 1994) is an effort to provide an overarching integration of previous theories in career counseling. Bandura's social cognitive theory (1986) is utilized as the primary foundation for the theory, which explores the complex ways in which people, behavior, and environmental surroundings jointly influence one another. SCCT recognizes the capacity for individuals to direct their own vocational behavior while also acknowledging personal and environmental influences that may strengthen, weaken, or negate human agency in career development.

The SCCT model utilizes three overarching person-centric variables to measure career development: self-efficacy beliefs, outcome expectations, and individual interest. The Choice Model within SCCT utilizes these constructs to help determine the likelihood of an individual majoring in a particular area. This research uses the SCCT Choice Model in the context of the multilevel nature of students nested within high schools.

School Size

The issue of school size has received much attention in research for many years. This issue is a contentious one, with some research suggesting that school consolidation is not a justified method as smaller schools are better for student learning (Baker et al. 2004; Lee et al. 1995), while research touting the economies of scale for larger schools has also been pushed for quite some time (Riew 1966). With regard to economies of scale, research has shown that the cost per student in a smaller school is higher in order to achieve similar outcomes (Bowles et al. 2002), with more of this money going to overhead of keeping the school running. Research shows that, had this per-pupil expenditure gone directly to the student, this would increase student achievement (Elliott 1998), which is typically a greater possibility at a larger school.

The question then becomes, what constitutes an optimal school size? Research has had various approaches and associated outcomes pertaining to this question. Early research used cost and output functions to place this optimal number of students at about 1500 pupils (Cohn 1968). Hierarchical linear modeling (HLM) analysis found the ideal number of students to be between 600 and 900 for learning effectiveness (Lee et al. 1997). More recent cost functions have found this optimal number to be 965 students (Charles et al. 2000) and a meta-regression analysis determined an optimal school size of around 1543 (Colegrave et al. 2008).

Less than 25 percent of the schools included in this research have greater than 1000 students with only three of these schools above the 1500 mark and all schools falling below the 2000 mark. Given the recommended optimal number of students in the studies above, we believe that the larger schools in our sample will have more money to spend towards student learning as opposed to costs of running the school, thereby providing greater learning opportunities, specifically with regards to technology, as compared to their smaller counterparts. We believe these technology-related opportunities will lead to a higher intent to major. Therefore, we hypothesize

H1: The larger the size of the school, the more likely an individual will major in IT.

Previous research has shown that interest positively influences intent to major (Carter 2006; Lent 2005) including the computing areas (Akbulut et al. 2008; Kim et al. 2002; Malgwi et al. 2005; McInerney et al. 2006; Zhang 2007). H1 would imply that interest would have a differing impact on intent to major for students depending on the size of the institution, specifically, that the impact of interest on intent to major should be greater for students at larger schools. Given this, we hypothesize

H2: The larger the size of the school, the more positive the impact of interest on intent to major in IT.

DATA COLLECTION

Subjects for this study were participants from a high school IT outreach program and subsequent competition held across the state and organized by a large Midwestern university. The program consisted of a year-long educational component culminating in a competition held by the host university in the spring. Three competition areas were utilized, coinciding with the areas of the program (cyber defense, game design, robotics). Schools could participate in one, two, or all three of the areas. The students were given challenges such as implementing a corporate network with specific services and securing this network, designing a dodge ball video game, or constructing a maze-traversing robot.

The survey for this research consisted of questions pertaining to the constructs in the SCCT model. Students were solicited by email to participate in the study during the fall of the school year just after they had signed up for the program. By surveying the students before the start of the program, this allowed for a cross-section of individuals who had not yet been introduced to the program, so the study could be a measure of initial student assessment without effects of the program confounding the results. The survey was offered online by providing students with a link to the survey sent in the solicitation email. Those who filled out the survey were entered into a drawing for an MP3 music player.

In total, 309 students completed the survey online. These students represented 40 different high schools from across the same state as the hosting university. The average number of respondents completing the survey from each high school was 7.7. The high schools ranged in size from 51 to 1992, with the average high school size being 587. From among the students, 31% were seniors, 30% juniors, 24% sophomores, and 15% freshman. Also, 83% of the respondents were male while the remaining 17% were female with most respondents describing themselves as Caucasian (92%). 95% of the sample showed some intent to go to either a two or four-year college upon graduation.

RESULTS

Measurement Model

Confirmatory factor analysis (CFA) using covariance-based SEM employing Mplus was used to evaluate the psychometric properties of the latent variables in the model. The measurement model included all the latent factors used in the research including the three subfactors of IT self-efficacy (cyber, game design, and robotics), outcome expectations, and interest. The second-order factor of IT self-efficacy was not estimated directly in the measurement model, but the three subfactors were instead extracted and correlated with the other latent variables in the model as directed by previous research (Bagozzi et al. 1994). The fit results from the measurement model had good fit [$\chi2(124) = 211.79$, $p < 0.001$, CFI = 0.97, TLI = 0.97, RMSEA = 0.048, SRMR = 0.041]. The means, standard deviations, Cronbach's alpha, composite reliabilities, average variance extracted (AVE), and correlations are given in Table 1.

						Correlations				
	Mean	Std. Dev	Alpha	CR	AVE	ITSE Cyber	ITSE Game	ITSE Robotics	Outcome	Interest
ITSE Cyber	3.16	1.56	0.88 [CI=0.86,0.91]	0.85	0.66	0.81				
ITSE Game	3.34	1.61	0.90 [CI=0.88,0.92]	0.90	0.76	0.76	0.87			
ITSE Robotics	4.25	1.61	0.87 [CI=0.82,0.88]	0.87	0.69	0.76	0.70	0.83		
Outcome	5.95	0.91	0.85 [CI=0.81,0.86]	0.85	0.58	0.68	0.62	0.70	0.76	
Interest	5.37	1.15	0.88 [CI=0.86,0.90]	0.88	0.60	0.74	0.70	0.65	0.60	0.77

Table 1. Means, standard deviations, Cronbach's alpha, composite reliability, average variance extracted (AVE), and correlations (with square root of AVE along the diagonal) of latent constructs in the measurement model.

The measurement model showed good reliability as values for Cronbach's alpha and composite reliability were all above the recommended level of 0.7 (Bagozzi et al. 1988; Bearden et al. 1993; Fornell et al. 1981; Nunnally 1978). The measurement model also showed good convergent validity as the lowest AVE value in the measurement model was above 0.5 and all items loaded on their respective latent variable above 0.7 (Chin 1998; Hair et al. 2006). Discriminant validity was also optimal as the square roots of the AVE values were all higher than the correlations of each construct with all other constructs in the measurement model (Chin 1998; Gefen et al. 2005; Majchrzak et al. 2005).

Research Models

Multilevel modeling (MLM) was used to test the proposed research, with Mplus (Muthén et al. 2011) software used due to its ability to estimate multilevel models. Each observed item for its respective construct was averaged to make a single observed item for the construct. Furthermore, group mean centering was used for the individual-level independent variables of ITSE, Interest, and Outcome Expectations, and grand mean centering was used for the group-level independent variable of school size.

First, to assess whether group differences are indeed apparent, we tested the base SCCT model, nesting students within schools, but not yet including the school-level covariate of school size. The -2 log likelihood for the model was found to be 1143.07 [6] (used to compare to later models). We found that there was a significant amount of variance unexplained at both the school level ($\tau11 = 0.42$, $p = 0.003$) and the individual level ($\sigma2 = 2.13$, $p < 0.001$). Calculating the intra-class correlation (ICC) value, we find that $\rho = 0.17$, indicating that about 17% of the variance in the data is between schools. Running a pseudo F-test, we find that this value is significant ($F = 1.57(39, 269)$, $p = 0.021$) allowing us to reject the hypothesis that the ICC is equal to zero and, therefore, accept that significant group differences exist.

Further examination shows the model was found to explain a significant amount of the variance in the dependent variable of Intent to Major ($R2 = 0.21$, $p < 0.001$). Additionally, the overall model showed significant standardized effects on Intent to Major from Interest ($\beta = 0.33$, $p < 0.001$) and Outcome Expectations ($\beta = 0.17$, $p = 0.005$), and a marginally significant effect from IT Self-Efficacy ($\beta = 0.07$, $p = 0.095$).

Second, size was added to the base model to test for its effect on Intent to Major (-2LL = 1137.55 [7]). A $\chi2$ difference test comparing this model to the model without the school-level covariate found the value decreased by 5.52 [1] ($p = 0.019$) indicating that this model fits significantly better than the base model without school size included. Second, we investigated the covariance parameters and found that there was a significant amount of variance unexplained at both the school level ($\tau11 = 0.31$, $p = 0.037$) and comparing these values to that of the first model, we find that the model including the school size covariate reduces the error variance between schools by 28%. Also, the unstandardized impact of the school-level covariate (school size) on Intent to Major showed significance (β = 0.52, p = 0.002), supporting H1.

A third model was used to assess whether the impact of interest differed between groups (i.e. random slope model) (-2LL = 1134.53 [9]). The χ2 difference test between this and the second model found a non-significant improvement in the model (Δχ2 = 3.02 [2], p = 0.22), thereby not supporting a difference in the impact of interest on intent to major between schools. Finally, a fourth model was used to assess whether school size affected the impact of interest between groups (i.e. cross-level interaction model) (-2LL = 1127.07 [10]). χ2 difference tests found a significant improvement in the model over both the second (Δχ2 = 10.48 [3], p = 0.015) and the third models (Δχ2 = 10.48 [3], p = 0.006). A significant effect of school size on the impact of interest on intent to major was also found, but this relationship is negative, supporting a differing impact on intent to major for students depending on the size of the institution, but opposite to H2. Instead, the effect of school size on the impact of interest on intent to major is greater for smaller schools. Figure 1 shows the final model with unstandardized weights.

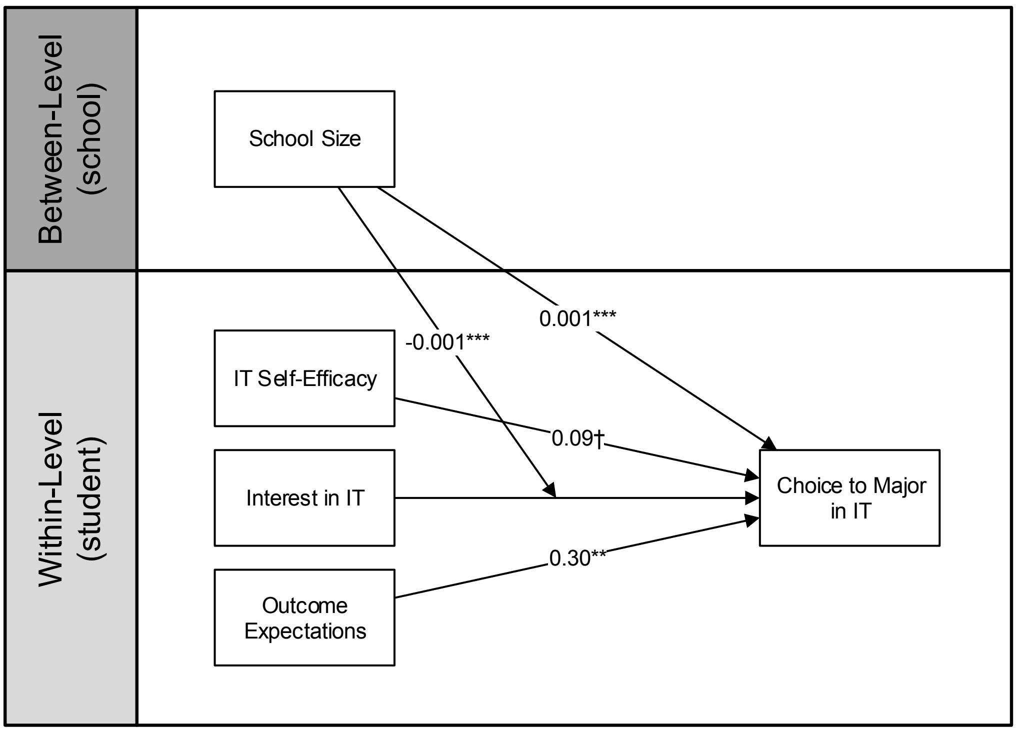

Figure 1. Full research model (model 4) (†p < 0.1, * p < 0.05, ** p < 0.01, ***p < 0.001).[1]

DISCUSSION

The enrollment crisis in IT continues to be a critical problem with lagging enrollments threatening both the major in colleges as well as corporations needing this expertise. Greater research is needed into IT as a major choice which we have provided using social cognitive career theory (Lent 2005; Lent et al. 1994) to help shed light on why individuals major in IT. The model builds on previous research by examining the impact of group-level contextual supports/barriers, specifically school size, on individual major choice.

When investigating student populations, the inherent hierarchical nesting of students within schools becomes an issue. Our research provides a more thorough approach to investigating intent to major in the context of school membership.

[1] When estimating a model with a random slope, standardized effects are not given, so those displayed in the diagram are *unstandardized*. This helps to explain why the effects of school size are so small and yet so highly significant. Each of the individual level variables are on a seven-point scale, but school size can vary up to around 2000 students. Furthermore, no beta is included for the effect of interest on intent to major as it is moderated by school size.

Furthermore, previous research has not used this approach with regard to the SCCT model. School size is one such aspect which has a demonstrated effect on educational outcomes for students (Bowles et al. 2002; Elliott 1998). We show that school size does indeed have a significant positive effect on learning outcomes in regards to intent to major in IT, with larger schools showing greater on-average student choice to major in IT. Research in economies of scale with regard to school size (Bowles et al. 2002; Elliott 1998) would suggest that due to less overhead administrative costs, larger schools have a greater amount of funds to dedicate towards computer equipment and specialized IT instructors.

While having a direct positive effect on intent to major, larger schools do not hold all the advantages. Our research shows that size has a negative moderating influence on the effect of interest on intent to major, contrary to our hypothesis. Specifically, the impact of interest on intent to major grows faster for smaller schools as compared to larger schools. This comes into play when we wish to implement programs to encourage students to major in IT. Our first model shows that Interest has a substantial effect on intent to major (standardized $\beta = 0.33$), so implementing programs to increase interest in IT should lead to greater intent to major in IT. Our research shows that, while this is true for everyone, increasing interest for students at a smaller school provides a greater associated increase in intent to major as compared to increasing interest for students at larger schools. So while students at larger schools start out at a higher level of intent to major (solid blue line in Figure 2), students at smaller schools have a greater associated increase in intent to major for an associated increase in interest (dashed green line in Figure 2). Therefore, programs to increase interest at smaller schools will have a greater impact on intent to major as compared to programs at larger schools (i.e. more “bang for your buck”). This provides very interesting insights for future research in the area.

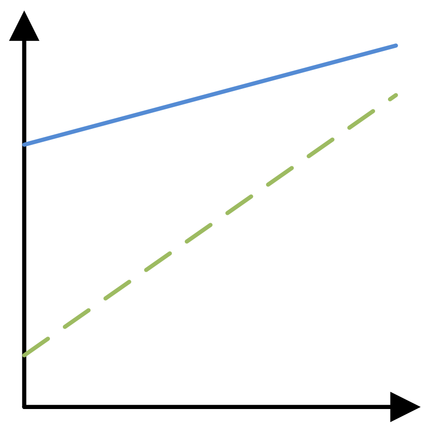

Figure 2. Cross-level interaction

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