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College-Based Career Interventions: Raising IT Employability and Persistence in Early Careers of IT Professionals

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ABSTRACT

The aims of the current study are twofold. First, we examine the relationship between specific modalities of career interventions and initial employment in IT. Specifically, we take a skills and social learning perspective to distinguish between direct and vicarious experiences of career interventions and relate these experiences to IT employability and career persistence. We test our predictions using data drawn from the National Longitudinal Survey of Youth, 1997. Our findings suggest that cooperative education, internship, and mentorship experiences increase the likelihood of initial IT employment. In addition, we find that internship and mentorship experiences engender persistence in IT careers. We discuss the implications our findings have on research and practice.

Keywords: Cooperative education, Internships & co-ops, Mentorship, Job shadowing, IT employability, Career persistence

1. INTRODUCTION

The bulk of the demand for information technology (IT) talent is traditionally met by graduating college IT majors. The US Bureau of Labor Statistics (BLS) projects that computing jobs will grow 12.8% from 2014 to 2024 (US Bureau of Labor Statistics, 2015). An estimated 500,000 IT professionals will be required to fill these jobs (US Bureau of Labor Statistics, 2015). Yet the IT labor market continues to experience talent shortage. Employers lament that IT students do not graduate with the “last mile” training and skills they need to be employable (Young, 2020). In addition, talented IT graduates continue to leave the IT profession in early stages of careers leading to higher rates of attrition (Joia & Sily de Assis, 2019).

Researchers, practitioners, and policymakers have decried the employability and attrition problem in early IT careers (Chen, 2013; The White House, 2016). Prescriptions to improve graduate employability and persistence in IT careers have led to wider implementations of career interventions in colleges (Jaradat, 2017). The implementation of college-based career interventions is motivated by the notion that new graduates are often underprepared for the real world of work and constrained by the lack of adequate work experience (Fang et al., 2005; Guzman & Stanton, 2009; Lee et al., 2002). So, do college-based career interventions facilitate initial employment and persistence in IT careers?

Research in IT career development suggests that college-based career interventions facilitate employment (Aasheim et al., 2009; Joseph, 2008). Findings from this stream of research crystalizes around the view that internship in particular prepares IT graduates with productive hands-on experience. Internship presumably bridges the IT skills gap that exists between the academic training process and the dynamic IT industry. While this research stream has contributed to our understanding of how career interventions facilitate favorable initial employment outcomes, the studies tend to narrowly focus attention on the employment outcomes of internships, much at the expense of other modalities of college-based career interventions. According to the career development literature, internships belong to a broader set of career interventions, which convey hands-on or direct experience. Social learning theory, however, hints that certain career interventions provide participants with vicarious experiences (Bandura & Walters, 1977; Herr & Watts, 1988). Vicarious modalities of career interventions require that work mentors, role models, and seasoned employees serve as conduits through which occupation-specific skills and information are conveyed to participants. Clearly, vicarious and direct modalities are conceptually distinct ways of conveying skills. Yet, little systematic research has simultaneously explored the relationship between direct and vicarious modalities of career interventions and IT employment outcomes. We contend that such an inquiry could extend our understanding of how each modality empirically relates to initial IT employment and thereby bring nuance to the broader discussion on career intervention.

Accordingly, the goals of the current study are two-fold. First, we adopt an inductive and quantitative approach to examine the relationship between vicarious and direct modalities of college-based career interventions and initial IT employment. Second, we examine the role the two modalities play in prompting persistence in early IT careers, i.e., the continuous pursuit of IT as a profession after graduating college.

2. CONCEPTUALIZING VICARIOUS AND DIRECT EXPERIENCES OF CAREER INTERVENTIONS

College-based career interventions prepare IT graduates for a future career in IT in terms of acquiring task-specific skills. The literature on experiential and social learning theory guides our thinking of how task-specific skills are conveyed via career interventions (Bandura & Walters, 1977; Kolb, 2014; Watts, 1996). Individuals acquire task-specific skills through hands-on or direct experience. Individuals may also acquire task-specific skills via observational learning and social interaction. Guided by the arguments flowing from the experiential and social learning literature, we argue that participants enrolled in a career intervention program may acquire task-specific skills by directly performing work or observing seasoned professionals perform work. Often, the two modes of skills acquisition are not exclusive to a specific modality of career intervention but rather they coexist. However, the degree of task-specific skills gained from a specific modality of career intervention may vary.

For example, internship (Callanan & Benzing, 2004), mentorship (Linnehan, 2001; Pan et al., 2011) and cooperative education (Fergusson et al., 2021) require participants to assume occupational roles and directly perform work-related tasks and functions over a sustained period. The degree of task-specific skills gained from these interventions are relatively high, resulting in a high direct experience. In contrast, other career interventions including job shadowing are less sustained (Rogers, 1996; Turner & Lapan, 2002). Job shadowing offers participants the opportunity to visit an occupational setting of interest and observe seasoned professionals perform their daily work tasks. The degree of task-specific skills gained from job shadowing is comparatively low because participants do not directly perform tasks, resulting in vicarious or low direct experience.

In sum, we contend that the degree of task-specific skills gained from the different modalities of career intervention lie on a continuum of low and high direct experiences. Low direct experience of career interventions conveys a relatively lower degree of task-specific skills whereas high direct experience of career interventions conveys more task-specific skills. Figure 1 presents our research model.

2.1 Research Question 1: Do Career Interventions Facilitate Initial Employment in IT?

Task-specific skills gained from college-based career interventions represent investments in IT human capital. Task-specific skills in IT are sine qua non for solving problems and completing tasks including computer programming, analysis and design of computer systems and networks (Huckman et al., 2009). Thus, the task-specific skills conveyed by career interventions increase task performance and future productivity in IT work.

Much of the organizational success and profitability that employers pursue relies on the productivity of their workforce (Bapna et al., 2013). As such, employers value individual productivity. They are likely to offer jobs to prospective workers who are endowed with productive human capital including task-specific skills gained from career interventions. Consistent with these arguments, it is conceivable that both vicarious and direct modalities of college-based career interventions will raise the employability of IT graduates as they transition into the IT labor market.

2.2 Research Question 2: Do Career Interventions Prompt Persistence in IT Careers?

As earlier argued, IT graduates develop occupation-specific skills after participating in career intervention programs. This development of occupation-specific human capital strengthens their occupational orientation in IT (Tomer & Mishra, 2016). Through college-based career interventions, IT graduates become confident in their skills and begin to identify more strongly with the occupation than they initially did (Pratt et al., 2006). Thus, their occupational identities become salient. To reaffirm the salient occupational identity, individuals engage in behaviors that are consistent with the norms and values of the profession (Callero, 1985; Stryker, 1980). The most proximal of such behaviors would be to remain in the IT profession and persist in IT careers.

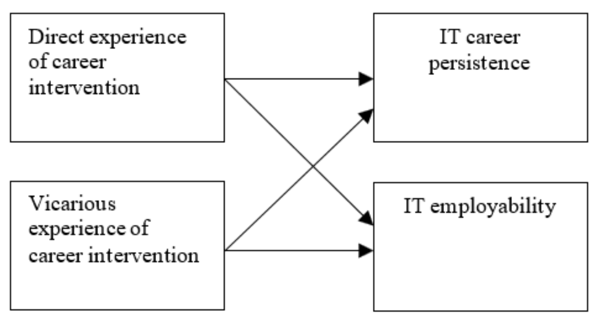

Figure 1. Research Model

3. METHODOLOGY

3.1 Data

To answer the aforementioned research questions, we analyze education and work history data of a sample of respondents drawn from the National Longitudinal Survey of Youth 1997 (NLSY97) cohort (US Bureau of Labor Statistics, 2016). The NLSY97 dataset is particularly suited for the present analysis for the following reasons. The NLSY97 documents young adult life transitions including youth entry into the labor force.

Furthermore, the NLSY97 cohort is a national representative sample. A representative sample reduces threats to external validity and increases the generalizability of the results (Cook et al., 1979).

The NLSY97 Survey. Sponsored and funded by the Department of Labor (DOL), the NLSY97 survey examines the lives of a sample of youthful Americans within the age range of 12 and 16 years as of December 31, 1996. The survey is administered by researchers from the National Opinion Research Center (NORC) under the auspices of the US Bureau of Labor Statistics. The researchers interview, administer questionnaires, and collect information about respondents in a longitudinal fashion.

The first round of the survey was administered in 1997 and followed a sample of 8,984 youthful Americans (Moore et al., 2000). The NLSY97 remains an active survey project which mostly runs annually. The NLSY97 collects extensive information on a broad range of topics such as educational experiences, demography, employment, and labor market activities. Employment data consists of variables including, but not limited to, a respondent's job start and stop dates, occupations, working hours, wages, job search activities, firm tenure, and job mobility. Educational data captures information about respondents' schooling history including dates of college enrollment and graduation, fields of study, enrollment into career interventions, academic performance, and degrees attained. Demographic and biographical data include birth dates, ethnicity, place of residence in the United States, and annual household income.

3.2 Research Question 1: Do Career Interventions Facilitate Initial Employment in IT?

3.2.1 Sample Construction. To estimate the influence of college-based career interventions on initial IT employment, a sample for the analysis is constructed from the universe of 8,984 NLSY97 respondents. Respondents qualify to be included in the study sample when they meet the following criteria. One, respondents must have attained an Associate's or Bachelor's degree in an IT field of study and provided the date of graduation. A respondent's field of study in the NLSY97 dataset is identified by the Classification Instructional Program (CIP) codes developed by the US National Center for Education Statistics (NCES). An IT degree includes the following: computer and information sciences, information technology, computer programming, computer information systems, computer systems analysis, computer/software engineering, and business/management information systems and data processing.

Two, respondents must have actively searched for a job after completing college. For all survey rounds, the NLSY97 asks respondents to report if they have actively searched for a job via one or more of the following methods: contacting employers directly, contacting employment agencies and sending out resumes or filling out job applications. These job search methods are denoted as active job searching because they may result in the offer of a job without any further action on the part of the job seeker.

Finally, respondents must have no record of IT employment before enrolling into college. This is to rule out the possibility that prior working experience in IT may influence employment at graduation. The NLSY97 provides both part-time and full-time employment information of respondents.

A total of 318 respondents met the three criteria. The final sample of 318 individuals consists of 219 (68.9%) males and 99 (31.1%) females. In regard to ethnicity, 58.8% are of Caucasians, 23.6% are African-Americans, and the remaining 17.6% are Hispanics or Mixed race. In terms of education credentials, 66.4% have attained a Bachelor's degree and 33.6% have attained an Associate's degree; 62.0% have attained degrees from public colleges and 38.0% have attained degrees from private colleges.

3.2.2 Data Analytical Approach. A survival analysis technique is used for the analysis. The dependent variable in survival analysis technique comprises two parts, i.e., the occurrence of the event and the event time (Allison, 2010). An event is defined as a qualitative change in state that involves a transition from one stage to another. The technique estimates two functions – the *survival* and *hazard* functions that describe the distribution of the event time. The survival function $S(t_i)$ is the probability that, for every unit time *t* within the period of observation, an individual *i* survives (or does not experience) the event of interest up to that time *t*. The hazard function $\lambda(t_i)$ is the likelihood that the event will occur on condition that the individual has survived the event up to the specified time *t*.

Survival analysis uses the Maximum Likelihood function (L) to estimate the parameters of the survival and hazard functions. The L function is the product of the survival and hazard functions. Thus, if an individual, *i*, experiences the event of interest at time t_i his or her contribution to the likelihood function is expressed as $L_i = S(t_i)\lambda(t_i)$.

A key strength of survival analysis over standard applications of ordinary least square (OLS) regressions is the capability to circumvent the limitations of censored observations (Allison, 1984). Censoring occurs when an individual either exits the study before the end of the observation period or does not experience the event before the end of the observation period. Failure to analytically incorporate censoring information in the estimation process could bias the results and threaten the interval validity of the study (Allison, 1984; Cook et al., 1979). Survival analysis carefully incorporates censoring information in the estimation process as follows. Recall that the hazard function $\lambda(t_i)$ is the likelihood that the event has occurred given that the individual has survived up to the time *t*. In cases of censoring, the event never occurs. Therefore, there is no hazard function $\lambda(t_i)$ for a censored observation. Thus, the contribution of a censored observation to the Likelihood function is $L_i = S(t_i)$ instead of $L_i = S(t_i)\lambda(t_i)$. By accounting for censoring in the estimation process, survival analysis technique produces unbiased estimates.

In the case of the current study, the event of interest is initial IT employment. Participants experience the event when they transition from college into IT jobs before the end of the observation period. The NLSY97 identifies jobs using the Standard Occupational Classification (SOC) codes (US Bureau of Labor Statistics, 2014). Table 1 presents the list of IT jobs identified in the NLSY97 data. Observations are censored when one of the following occurs: (1) participants transition into non-IT job roles, or (2) participants do not enter the labor market before the end of the sampling period. Figure 2 provides an example of the data structure and how the current study treats college graduation to IT employment transition and censoring.

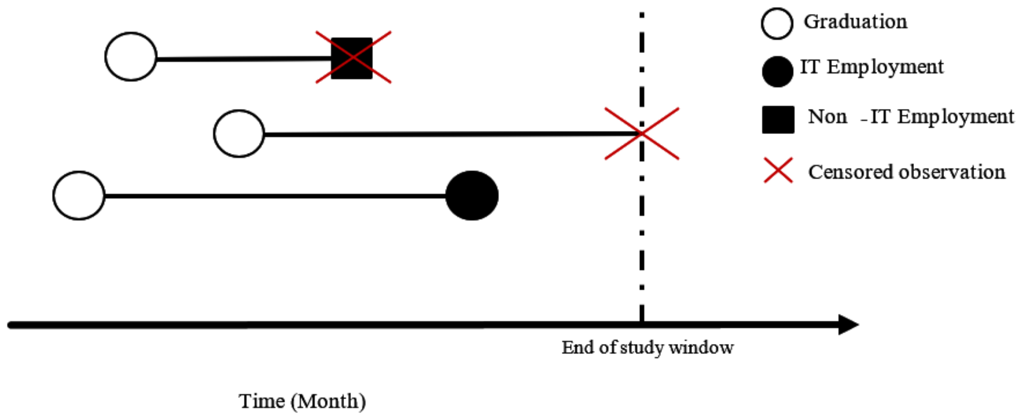

Figure 2. College Graduation-IT Employment Transition and Censoring

OCS Code	Job Title
1000	Computer Systems Analyst
1010	Computer Programmer
1020	Computer Software Engineer
1040	Computer Support Specialist
1060	Database Administrator
1100	Network and Computer Systems Administrator
1110	Network Systems and Data Communication Analyst
1400	Computer Hardware Engineer

Table 1. Occupation Classification Codes (OCS) and NLSY97 Job Titles

3.2.3 Measures. Dependent Variable: The dependent variable is the hazard risk to initial IT employment. The hazard risk to initial IT employment is the likelihood that an individual finds IT employment at graduation.

Explanatory Variables: The explanatory variables are direct and vicarious career interventions. The NLSY97 asks respondents if they participated in a work-based learning program at school. We consider work-based learning programs at the college level. These are cooperative education, internship, mentorship, and job shadowing.

Direct Career Intervention. *Cooperative Education* (CoopExp), *Mentorship* (MentorExp), and *Internship* (InternExp) are direct experiences of career interventions. Cooperative education experience is measured with a dichotomous variable: "1" if respondent enrolled in cooperative education and "0" if respondent did not enroll in the program. Mentorship experience is also measured with a dichotomous variable: "1" if respondent participated in a mentorship program and "0" if respondent did not participate in the program. Internship experience is a dichotomous variable as well: "1" if respondent participated in an internship and "0" if respondent did not participate in the program.

Vicarious Career Intervention. *Job Shadowing* (JobShadExp) is a vicarious experience of career interventions. Job shadowing experience is measured as a dichotomous variable: "1" if respondent participated in a job shadowing program and "0" if respondent did not participate in the program.

Control Variables: Guided by prior research, we included a series of control variables in the model. To account for the possible influence of individual aptitude on the likelihood of initial IT employment, we controlled for *Cognitive Ability* and *Academic Performance* (Brown et al., 2004; Pinto & Ramalheira, 2017). Cognitive ability (CogAbility) is a measure of the Armed Services Vocational Aptitude Battery (ASVAB) scores. The NLSY97 administered a computer-adaptive version of the ASVAB test to respondents in the first round of the survey. The ASVAB measures a respondent's aptitude in the following areas: arithmetic reasoning, assembling objects, auto information, coding speed, electronics information, general science, mathematics knowledge, mechanical comprehension, numerical operations, paragraph comprehension, shop information, and word knowledge.

Academic performance (AcadPerf) is a standardized measure of the final Grade Point Average (GPA). GPA is measured on a 4-point scale. Academic performance and cognitive ability variables are logged for easier interpretation. *Education level* (EduLevel) is a dichotomous variable coded as "1" if respondent attains a bachelor's degree and "0" if respondent attains an associate degree. *College Type* (ColType) is coded as "1" if respondents graduated from a public college and "0" if respondents graduated from a private college. Ethnicity is a categorical variable ("1" = Caucasian, "2" = African-American, and "0" = Other). *Sex* is coded as "1" = Male and "0" = Female. *Socioeconomic Status* (SES) is a logged measure of the annual household income (USD) of a respondent. Household income is adjusted for inflation using the consumer price index (CPI) deflator with 2019 as the base year.

Guided by the job search literature, we accounted for the potential effect of median wage rate of a job on the likelihood of initial IT employment. The theory of optimal stopping as applied in the job search literature posits that the period of job search or unemployment is contingent on the wage rate individuals believe is commensurate with their human capital endowment (McCall, 1970; Mortensen, 1970). A candidate would reject job offers, which do not maximize expected earnings, and remain unemployed (McCall, 1970).

Median Wage Rate (MedianWageRate) is a measure of the industry median hourly rate of pay (USD) for a focal IT job role.

Median wage rate is adjusted for inflation using the CPI deflator with 2019 as the base year. The BLS provides estimates of the weekly and hourly median rate of pay of jobs. The estimates are calculated with data collected from employers in all the occupations identified by the SOC codes.

To account for the year-on-year employment situation in the US, the official unemployment rate for the corresponding year that a respondent graduated college was included in the model. *Yearly Unemployment Rate* (YUR) is the ratio of the number of unemployed persons who are actively looking for a job to the total number of employed and unemployed people in each year expressed as a percentage. We also controlled for the geographic location of a respondent in the United States. *Region* is a four-level categorical variable ("1" = North Central; "2" = South; "3" = West, and "0" = South). Further, urban and rural residents are coded ("1" = Urban; "0" = Rural). All categorical variables coded as "0" are reference categories.

We controlled for the duration of the intervention program. *Duration of College-Based Career Intervention* (DurationCBCI) is a measure of the total number of months an individual participated in one or more of the college-based career interventions. We decided against controlling for the effect of career intervention remuneration. This decision is informed by the presence of multicollinearity. Cooperative education experience is perfectly correlated with the dummy variable that captures whether respondents received pay for participating in any of the college-based career interventions.

3.2.4 Empirical Model. Equation 1 presents the empirical model. The hazard risk to initial IT employment λ at a time t is expressed as a function of the substantive explanatory and control variables.

$$log\ log\ \lambda\,(t)\ =\ \beta_0 + \beta_1 YUR + \beta_{2-4} Region + \beta_5 Urban + \beta_6 Sex + \beta_{7-8} Ehnicity + \beta_9 SES + \beta_{10} CollegeType + \beta_{11} EduLevel + \beta_{12} AcadPerf + \beta_{13} CogAbility + \beta_{14} MedianWageRate + \beta_{15} DurationCBCI + \beta_{16} CoopExp + \beta_{17} InternExp + \beta_{18} MentorExp\ + \beta_{19} JobShadExp \quad \text{Equation [1]}$$

3.2.5 Results. Table 2 presents the descriptive statistics and correlations of the variables. Table 3 shows the results of the survival analysis.

Direct Career Intervention and initial IT Employment. Results from Table 3 indicate that the relationship between cooperative education and the hazard risk to initial IT employment success is positive and significant ($\beta_{16} = 0.902, t = 2.550, p < 0.05$). The hazard ratio indicates that a unit increase in cooperative education increases the likelihood of initial IT employment by a factor of 2.5.

Results from Table 3 indicate that the relationship between internship and the hazard risk to initial IT employment is positive and significant ($\beta_{17} = 0.418, t = 2.150, p < 0.05$). The hazard ratio indicates that internship increases the likelihood of initial IT employment by a factor of 1.5. Results from Table 3 indicate that the relationship between mentorship and the hazard risk to initial IT employment is positive and significant ($\beta_{18} = 0.610, t = 2.940, p < 0.01$). The hazard ratio indicates that mentorship experience increases the likelihood of initial IT employment by a factor of 1.8.

Vicarious Career Intervention and Initial IT Employment. Results from Table 3 indicate that the relationship between job shadowing and the hazard risk to IT employment is negative but not significantly different than zero ($\beta_{19} = -0.123, t = -0.290, n.s.$).

3.3 Do Career Interventions Prompt Persistence in IT Careers?

We collected work history observations of the 318 individuals from the NLSY97 dataset. These observations represent the series of full-time jobs held by individuals. The NLSY97 considers a full-time job as any job that is more than 35 hours per week. The work history observations begin in the survey round an individual entered the labor force at graduation and are observed at a yearly frequency till the end of the last survey round. Individuals contributed multiple work history observations, resulting in an unbalanced longitudinal dataset. The total number of person-period observations in the sample is 1,676.

3.3.1 Measures. Dependent Variable: The dependent variable is *IT Career Persistence* (CP). IT career persistence is operationalized as the cumulative number of years spent in IT job roles.

Explanatory Variables: The explanatory variables are direct and vicarious career interventions. *Cooperative Education, Mentorship, and Internship* experience are direct career interventions. *Job Shadowing* is a vicarious career intervention. Cooperative education, internship, mentorship, and job shadowing experiences are dichotomous variables coded as "1" if a respondent participated in a focal program and "0" if a respondent did not participate in the program while in college.

Control Variables: We included a series of variables to rule out alternative explanations for IT career persistence. We controlled for *Cognitive Ability* and *Academic Performance*. The rationale for including cognitive ability and academic performance as control variables stems from the idea that the IT profession is a knowledge-intensive discipline. IT professionals who have demonstrable knowledge and aptitude may thrive more and show greater persistence in IT careers. Cognitive ability is the logged measure of the ASVAB test scores. Academic performance is a measure of the final GPA. In addition, we controlled for *Education Level* ("1" = Bachelor's degree; "0" = Associate's degree) and *College Type* ("1" = Public College; "0" = Private College). Prior research has demonstrated that social minorities in the US including African-Americans and females are less persistent in STEM careers (Cech et al., 2011). Accordingly, we controlled for *Sex* and *Ethnicity*. Sex is coded as "1" = Male; "0" = Female. Ethnicity is coded as "1" = Caucasian; "2" = African-American; "0" = Hispanics or Mixed Race.

Holland's (1997) study on personality-job congruence opines that individuals tend to remain in careers that conform with their personality orientation. Further evidence from personality research in IT suggests that traits of extraversion and emotional resilience are associated with increased levels of career satisfaction (Lounsbury et al., 2007). In view of this, we controlled for traits of *Extraversion* and *Emotional Resilience*. The NLSY97 collects information on personality traits. Respondents rate how well extraversion and emotional resilience personality traits are applicable to them on a 7-point Likert scale ("1" = Disagree strongly … "7" = Agree strongly).

		Mean	SD	1	2	3	4	5	6	7	8	9
1	Survival Time (Unemployment period)	5.758	5.492									
2	Yearly Unemployment Rate	5.699	1.496	0.077								
3	Region: North Central	0.230	0.421	0.023	0.044							
4	Region: South	0.358	0.480	0.021	-0.009	-0.408**						
5	Region: West	2.579	1.035	0.074	-0.002	-0.306**	0.305**					
6	Urban	0.796	0.404	-0.605**	-0.083	0.036	-0.076	-0.154**				
7	Sex: Male	0.689	0.464	-0.119*	-0.060	0.092	-0.064	0.035	0.063			
8	Ethnicity: Caucasian	0.588	0.493	-0.098	-0.008	0.244**	-0.240**	-0.075	0.114*	0.182**		
9	Ethnicity: African-American	0.236	0.425	-0.019	-0.029	-0.145**	0.388**	-0.017	-0.067	-0.154**	-0.664**	
10	Socioeconomic Status	10.996	0.957	-0.124*	-0.065	0.019	-0.067	0.008	0.036	0.072	0.079	-0.114*
11	Public College	0.620	0.486	-0.018	0.052	0.012	0.046	0.113*	0.036	0.005	0.055	0.008
12	Bachelor's Degree	0.664	0.473	-0.112*	-0.104	-0.039	-0.078	-0.059	0.002	0.053	0.148**	-0.075
13	Academic Performance	3.207	0.536	-0.343**	-0.075	0.039	-0.077	-0.063	0.203**	0.012	0.111*	-0.089
14	Cognitive Ability	10.923	0.577	-0.018	-0.059	0.092	-0.151**	-0.048	0.092	0.069	0.374**	-0.344**
15	Median Wage Rate	27.581	25.327	-0.192**	-0.026	-0.023	0.013	0.034	0.106	0.104	0.030	0.004
16	Duration of College-Based Career Intervention	2.179	2.441	-0.518**	-0.058	0.049	-0.066	-0.086	0.316**	0.016	0.046	0.011
17	Cooperative Education Experience	0.053	0.225	-0.153**	0.032	0.003	-0.032	-0.092	0.120*	0.069	0.000	0.033
18	Internship Experience	0.450	0.498	-0.463**	-0.158**	-0.058	-0.017	-0.023	0.380**	0.034	-0.001	0.004
19	Mentorship Experience	0.387	0.488	-0.531**	-0.075	-0.080	0.053	-0.076	0.274**	-0.052	-0.017	0.106
20	Job Shadowing Experience	0.063	0.243	0.231**	0.002	-0.018	-0.032	0.106	-0.094	-0.050	-0.099	-0.022

		10	11	12	13	14	15	16	17	18	19
1	Survival Time (Unemployment period)										
2	Yearly Unemployment Rate										
3	Region: North Central										
4	Region: South										
5	Region: West										
6	Urban										
7	Sex: Male										
8	Ethnicity: Caucasian										
9	Ethnicity: African-American										
10	Socioeconomic Status										
11	Public College	-0.111*									
12	Bachelor's Degree	0.124*	-0.065								
13	Academic Performance	0.057	-0.127*	0.096							
14	Cognitive Ability	0.109	0.117*	0.277**	0.083						
15	Median Wage Rate	0.146**	0.049	0.171**	0.136*	0.112*					
16	Duration of College-Based Career Intervention	0.080	-0.006	0.093	0.248**	-0.001	0.165**				
17	Cooperative Education Experience	0.081	-0.015	0.051	0.167**	0.020	0.045	0.160**			
18	Internship Experience	0.070	-0.008	0.135*	0.159**	0.052	0.089	0.403**	-0.038		
19	Mentorship Experience	0.111*	-0.016	0.101	0.203**	0.028	0.204**	0.535**	-0.098	0.385**	
20	Job Shadowing Experience	-0.059	0.043	-0.062	-0.093	-0.045	-0.007	0.093	-0.004	-0.026	-0.046

N = 318; SD = Standard Deviation; Survival Time denotes the time (in months) it takes an individual to enter the IT labor market. * $p < 0.05$; ** $p < 0.01$

Table 2. Descriptive Statistics and Correlations - College-Based Career Interventions and Initial IT Employment

It is conceivable to argue that in the face of chronic stress caused by job-specific stressors (e.g., long working hours) IT professionals may withdraw from IT careers (Shropshire & Kadlec, 2012). Accordingly, we controlled for work overload using *Working Hours*. Working hours is a lagged (t-1) measure of the number of weekly working hours. *Industry Type* is a lagged categorical variable (Professional, Business, or Finance; "2" = Retail and Trade industry; "3" = Manufacturing and "0" = Other industries). Lagging variables increase the predictive power of the variables and reduce the possibility of simultaneity bias between independent and dependent variables (Singer & Willett, 1991).

We controlled for *Job Satisfaction* levels and *Wage Rate*. Job satisfaction and wage rate are lagged measures. The NLSY97 asks respondents to rate how they feel about their current job on a (reverse coded) 5-point Likert scale ("1" = Dislike it very much … "5" = Like it very much). Wage rate is a measure of the hourly rate of pay adjusted for inflation using the CPI deflator with 2019 as the base year.

3.3.2 Data Analytical Approach. For the current analysis, we use a random effects Tobit panel regression (with censoring at zero) to estimate the predictors of IT career persistence. Tobit regression accounts for censored distribution by combining the probit likelihood of observing censored observation with the linear regression likelihood to explain uncensored observation, thereby resulting in consistent estimates (Greene, 2000). The dependent variable IT Career Persistence, CP, is left-censored at zero. CP is either zero or a positive number. We estimate the empirical model by specifying the (uncensored) dependent variable CP_{it}^{*} as a function of the regressors, an idiosyncratic error ε_{it} and individual-specific error α_i. The empirical model is estimated at the person-period unit of analysis.

$$\begin{aligned} CP_{it}^{*} = \beta_0 + \beta_1 WorkingHours_{i,t-1} & \\ + \beta_2 JobSatisfaction_{i,t-1} & \\ + \beta_3 Wages_{i,t-1} & \\ + \beta_{4-6} IndustryType_{i,t-1} & \\ + \beta_7 AcademicPerformance_i & \\ + \beta_8 CognitiveAbility_i + \beta_9 EduLevel_i & \\ + \beta_{10} CollegeType_i + \beta_{11} Sex_i & \\ + \beta_{12-13} Ethnicity_i + \beta_{14} Extraversion_i & \\ + \beta_{15} EmotionalResilience_i & \\ + \beta_{16} CoopExp_i + \beta_{17} InternExp_i & \\ + \beta_{18} MentorExp_i & \\ + \beta_{19} JobShadowExp_i + \alpha_i + \varepsilon_{it}; & \end{aligned}$$

		Dependent Variable: Hazard Risk to Initial IT Employment					
Control Variables		Estimate	se	t value	95%[CI]		HR
Intercept	β_0	-14.037***	2.188	-6.410	-18.326	-9.748	0.000
Yearly Unemployment Rate	β_1	-0.026	0.050	-0.510	-0.124	0.073	0.975
Region: North Central	β_2	-0.614**	0.201	-3.050	-1.009	-0.219	0.541
Region: South	β_3	-0.036	0.187	-0.190	-0.402	0.330	0.965
Region: West	β_4	-0.075	0.078	-0.960	-0.228	0.079	0.928
Urban	β_5	1.900***	0.322	5.910	1.270	2.531	6.688
Sex: Male	β_6	-0.380*	0.168	-2.270	-0.708	-0.051	0.684
Ethnicity: Caucasian	β_7	-0.168	0.208	-0.810	-0.575	0.239	0.845
Ethnicity: African-American	β_8	0.068	0.262	0.260	-0.445	0.582	1.071
Socioeconomic Status	β_9	0.088	0.082	1.080	-0.072	0.249	1.092
Public College	β_{10}	0.243	0.164	1.480	-0.078	0.564	1.275
Bachelor's Degree	β_{11}	0.274	0.178	1.540	-0.074	0.622	1.315
Academic Performance	β_{12}	0.098	0.152	0.650	-0.199	0.396	1.103
Cognitive Ability	β_{13}	-0.003	0.150	-0.020	-0.298	0.291	0.997
Median Wage Rate	β_{14}	0.002	0.002	0.880	-0.002	0.006	1.002
Duration of College-Based Career Intervention	β_{15}	0.174**	0.061	2.840	0.054	0.294	1.190
Explanatory Variables							
Direct Career Intervention							
Cooperative Education Experience	β_{16}	0.902*	0.354	2.550	0.207	1.596	2.464
Internship Experience	β_{17}	0.418*	0.194	2.150	0.037	0.798	1.518
Mentorship Experience	β_{18}	0.610**	0.207	2.940	0.204	1.017	1.841
Vicarious Career Intervention							
Job Shadowing Experience	β_{19}	-0.123	0.425	-0.290	-0.956	0.709	0.884
N				283			
Log Likelihood				-201.439			
df				20			
AIC				442.878			
Wald χ² (18)				356.650***			

* *p* < 0.05; ** *p* < 0.01 ****p* < 0.001; se denotes the robust standard errors; CI denotes the confidence intervals of the estimates.

Table 3. Results of the Survival Analysis

where $\varepsilon_{it} \sim N\,(0, \sigma_{\varepsilon}^2)$ and $\alpha_i \sim N\,(0, \sigma_{\alpha}^2)$

$$CP_{it} = \begin{cases} CP_{it}^{*}, if\ CP_{it}^{*} > 0 \\ 0, if\ CP_{it}^{*} = 0 \end{cases}$$

Equation [2]

where *i* indexes individuals; t-1 indexes one-year lag relative to nth year in the labor force.

3.3.3 Results: Table 4 presents the descriptive statistics and correlations for the study of college-based career intervention and IT career persistence. Table 5 presents the results of the Tobit panel regression analysis.

Direct Career Intervention and IT Career Persistenc*e*: Results from Table 5 indicate that the relationship between cooperative education and IT career persistence is positive but not significant ($\beta_{16} = 0.531, t = 1.770, n.s.$). Results from Table 5 indicate a positive and significant relationship between internship and IT career persistence ($\beta_{17} = 0.500, t = 3.220, p < 0.05$). Results from Table 5 indicate a positive and significant relationship between mentorship and IT career persistence ($\beta_{18} = 0.845, t = 5.340, p < 0.001$).

Vicarious Career Intervention and IT Career Persistenc*e*: Results from Table 5 indicate that the relationship between job shadowing and IT career persistence is negative but not significant ($\beta_{19} = -0.290, t = -0.980, n.s.$).

3.4 Discussion

The current research examines the role college-based career interventions play in determining initial IT employment and IT career persistence. College-based career interventions comprise of direct and vicarious modalities. Direct career interventions include cooperative education, mentorship, and internship. Vicarious career intervention includes mentorship and job shadowing.

		Mean	SD	1	2	3	4	5	6	7	8
1	IT Career Persistence	2.920	2.456								
2	Working Hours $_{t-1}$	40.920	0.021	0.021							
3	Job Satisfaction $_{t-1}$	3.080	0.910	-0.039	-0.058*						
4	Wage $_{t-1}$	26.131	92.491	-0.010	0.004	-0.057*					
5	Industry Type $_{t-1}$: Professional, Business or Finance	0.700	0.461	0.022	0.028	0.025	0.031				
6	Industry Type $_{t-1}$: Retail & Trade	0.130	0.335	-0.023	0.105**	-0.121**	-0.024	-0.576**			
7	Industry Type $_{t-1}$: Manufacturing	0.110	0.319	-0.052	-0.112**	0.087**	-0.007	-0.544**	-0.139**		
8	Academic Performance	3.207	0.536	0.093**	0.051	-0.062*	-0.034	-0.005	0.108**	-0.040	
9	Cognitive Ability	10.923	0.577	0.014	0.136**	-0.054*	-0.038	-0.052	0.083**	-0.019	0.072**
10	Bachelor's Degree	0.664	0.473	-0.027	0.183**	-0.019	-0.008	-0.055*	0.110**	-0.009	0.086**
11	Public College	0.620	0.486	-0.107**	-0.057*	0.010	0.022	-0.076**	0.030	0.099**	-0.070**
12	Sex: Male	0.689	0.464	0.028	0.082**	-0.009	0.037	0.159**	-0.094**	-0.045	0.000
13	Ethnicity: Caucasian	0.588	0.493	-0.022	0.122**	-0.053	-0.003	0.066*	0.032	-0.045	0.070**
14	Ethnicity: African-American	0.236	0.425	0.036	-0.054*	0.123**	-0.042	-0.088**	-0.055*	0.037	-0.041
15	Extraversion	5.260	1.318	-0.011	0.006	0.004	0.043	-0.102**	0.061*	0.075**	-0.057*
16	Emotional Resilience	5.760	1.214	0.051*	0.007	-0.032	0.031	-0.077**	0.042	0.036	0.041
17	Cooperative Education Experience	0.053	0.225	0.050*	0.000	0.022	-0.014	-0.002	0.024	0.017	0.132**
18	Internship Experience	0.450	0.498	0.124**	-0.007	0.005	0.030	0.027	-0.025	0.048	0.102**
19	Mentorship Experience	0.387	0.488	0.160**	0.017	-0.045	-0.017	-0.028	0.008	0.036	0.165**
20	Job Shadowing Experience	0.063	0.243	-0.026	-0.028	0.043	-0.024	0.020	-0.013	-0.021	-0.067**

		9	10	11	12	13	14	15	16	17	18	19
1	IT Career Persistence											
2	Working Hours $_{t-1}$											
3	Job Satisfaction $_{t-1}$											
4	Wage $_{t-1}$											
5	Industry Type $_{t-1}$: Professional, Business or Finance											
6	Industry Type $_{t-1}$: Retail & Trade											
7	Industry Type $_{t-1}$: Manufacturing											
8	Academic Performance											
9	Cognitive Ability											
10	Bachelor's Degree	0.318**										
11	Public College	0.109**	-0.040									
12	Sex: Male	0.036	-0.011	-0.003								
13	Ethnicity: Caucasian	0.356**	0.135**	0.063**	0.183**							
14	Ethnicity: African-American	-0.331**	-0.101**	0.017	-0.149**	-0.672**						
15	Extraversion	-0.070**	-0.040	-0.083**	-0.002	-0.187**	0.156**					
16	Emotional Resilience	0.097**	0.027	0.013	0.065**	0.011	0.029	0.091**				
17	Cooperative Education Experience	-0.013	0.007	0.017	0.066**	-0.031	0.100**	0.024	0.052*			
18	Internship Experience	0.028	0.143**	0.019	0.079**	0.001	0.029	-0.054*	0.044	-0.014		
19	Mentorship Experience	0.013	0.105**	-0.032	-0.037	-0.022	0.112**	-0.013	-0.022	-0.070	0.391**	
20	Job Shadowing Experience	-0.108**	-0.116**	0.057*	-0.064**	-0.096**	-0.005	-0.083**	-0.003	-0.006	-0.039	-0.034

Correlations are based on lagged N = 1358; SD = Standard Deviation; * $p < 0.05$; ** $p < 0.01$.

Table 4: Descriptive Statistics and Corrections – College-Based Career Interventions and IT Career Persistence

Dependent Variable: IT Career Persistence						
Control Variables		Estimate	se	t value	[95%CI]	
Intercept	β_0	-0.551	1.626	-0.340	-3.740	2.638
Working Hours$_{t-1}$	β_1	0.009	0.010	0.940	0.010	0.029
Job Satisfaction$_{t-1}$	β_2	0.044	0.077	0.570	-0.108	0.196
Wage Rate$_{t-1}$	β_3	0.000	0.001	0.020	-0.002	0.002
Industry Type: Professional, Business or Finance$_{t-1}$	β_4	-0.768*	0.299	-2.570	-1.354	-0.182
Industry Type: Retail & Trade$_{t-1}$	β_5	-0.777*	0.346	-2.240	-1.456	-0.097
Industry Type: Manufacturing$_{t-1}$	β_6	-1.047**	0.346	-3.030	-1.726	-0.368
Academic Performance	β_7	0.417**	0.134	3.120	0.155	0.679
Cognitive Ability	β_8	0.191	0.138	1.390	-0.079	0.462
Bachelor's Degree	β_9	-0.435**	0.159	-2.730	-0.747	-0.123
Public College	β_{10}	-0.668***	0.147	-4.550	-0.956	-0.380
Sex: Male	β_{11}	-0.218	0.161	-1.350	-0.098	0.534
Ethnicity: White	β_{12}	-0.237	0.202	-1.170	-0.632	0.159
Ethnicity: African-American	β_{13}	-0.043	0.237	-0.180	-0.508	0.423
Extraversion	β_{14}	-0.086	0.055	-0.420	-0.194	0.023
Emotional Resilience	β_{15}	0.100	0.059	0.810	-0.016	0.216
Explanatory Variables						
Direct Career Intervention						
Cooperative Education Experience	β_{16}	0.531	0.300	1.770	-0.058	1.120
Internship Experience	β_{17}	0.500**	0.155	3.220	0.196	0.805
Mentorship Experience	β_{18}	0.845***	0.158	5.340	0.534	1.155
Vicarious Career Intervention						
Job Shadowing Experience	β_{19}	-0.290	0.294	-0.980	-0.867	0.288
Wald χ^2 (19)		339.020				
Log Likelihood		-3657.568				

* $p < 0.05$; ** $p < 0.01$*** $p < 0.01$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.
t-1 one-year lagged variable

Table 5. Results of the Tobit Panel Regression

3.4.1 College-Based Career Interventions and Initial IT Employment: We find that career interventions – internship, mentorship, and cooperative education that convey direct or hands-on experience raise the employability of IT graduates on the job market. These findings are consistent with human capital theory and prior research, which have demonstrated that participation in some form of experiential job training program ranks high on recruiters' criteria for hiring new graduates (Zhao & Liden, 2011).

We do not find support for the prediction that vicarious experience gained from job shadowing raises graduate employability in IT. A possible explanation for the non-significant finding could be that IT employers do not consider job shadowing to be an effective intervention for transferring task-specific skills. Job shadowing is more suited to aspirants to occupations for which motor skills acquisition and reproduction form an instructive component of the job-learning and skills development process (Gioia & Manz, 1985; Goldstein, 1980). IT work, however, requires more than just motor skills. Job shadowing, therefore, may be of limited effectiveness in transferring knowledge-based occupations including the IT profession.

3.4.2 College-Based Career Interventions and IT Career Persistence: Our study finds that some modalities of career interventions prompt persistence in early IT careers. Specifically, IT graduates with internship and mentorship experiences tend to stay in the IT careers. The finding echoes evidence from adjacent research, which investigates the role professional associations play in retaining young computing professionals. Umapathy and Ritzhaupt (2011) argue that senior members of professional associations mentor and support young computing professionals with their professional development and this aids them in forging professional identities in IT. Forging professional identities in IT increases professional commitment to IT careers.

Surprisingly, we do not find evidence that cooperative education increases persistence in IT careers. We suspect that the lack of finding could be attributed to notions that IT professionals with in-depth skills and knowledge are viable candidates for internal mobility programs aimed at seeding business units with IT knowledge (Reich & Kaarst-Brown, 1999). Cooperative education programs are comprehensive at conveying in-depth skills and as a result these graduates may be transferred to low-level non-IT management roles in the business units to disseminate IT knowledge.

We also do not find evidence that job shadowing increases career persistence in IT. Unlike mentorship programs, job shadowing occurs over a shorter period. Thus, job shadowing does not aid participants to forge professional identities that prompt career persistence in IT.

3.5 Implications for Research

Our study provides several points of departure from prior research that has explored the employment outcomes of career interventions. First, we introduce the notion of vicarious experiences of career interventions. We synthesize and build insights from social learning theory to theorize that career interventions not only convey direct experiences, but also occupational knowledge and skills may be transmitted vicariously. The introduction of the concept of vicarious experience of career interventions complements existing research (*see* Narayanan et al., 2010) that has lopsidedly examined how direct experiences of career interventions including internships influence career outcomes.

Our second point of departure is the shift from examining proximal outcomes (e.g., employability) of career intervention experiences, which have been the focus of the extant research, to a distal outcome – career persistence. Although we acknowledge the relevance of linking career intervention experiences to employment outcomes, we see an unmet need of exploring the distal outcomes of career intervention experiences. We synthesize concepts from the occupational socialization and identity theory to theorize that career intervention experiences may prompt persistence in IT careers. In doing so, we enrich the career skills development literature by extending the nomological network of career interventions to include career persistence as an antecedent of career intervention experiences.

Finally, whereas the primary aim of our study is to provide an original contribution to the career development literature, we also see our work as linked to conversations in the IT mobility literature. IT mobility literature identifies career burnout, stress, and relative pay gap as the enablers of turnaway behaviors (Armstrong et al., 2015; Joseph et al., 2015). By identifying how specific modalities of career interventions engender persistence in the early careers of IT professionals, we contribute a new perspective on the longstanding conversations in the IT mobility literature regarding the factors that influence IT professionals to remain in the IT profession or careers. Our study highlights that the conversation becomes more comprehensive when we acknowledge that complementing academic training with internships and mentorships equips IT graduates with the professional skills required to thrive in early careers.

We would welcome future research that extends our work to consider the employability implications of career intervention characteristics. We suspect that career intervention characteristics including compensation and quality of supervision could moderate the relationship between career intervention experiences and initial employment. These characteristics provide additional signals to potential employers regarding the future productivity IT graduates.

3.6 Implications for Practice

Our study has important implications for Institutes of Higher Learning (IHL), IT students, and policymakers. IHLs may benefit from the findings of the study in educating and elevating students' awareness about career skills development and employability at graduation. Given budgetary constraints, findings of the study could inform administrators of IHLs of the relative efficacies of direct and vicarious modalities of career interventions in determining employability. For IT students, the results reported in the current study should encourage them to participate in career interventions to facility entry into IT careers.

Policymakers should be aware that career interventions enable newly-minted IT graduates to persist in early IT careers. Public agencies that are responsible for ensuring a sustainable flow of IT talents to meet the current and future demand for IT manpower may benefit from the findings of our study. The findings could inform policy positions that based on IT attrition concerns.

4. CONCLUSION

Our study investigates the effect of different modalities of career intervention – cooperative education, internship, job shadowing, and mentorship – on employability and career persistence in IT. Our findings suggest that cooperative education, internship, and mentorship experiences increase the likelihood of initial IT employment. In addition, we find that internship and mentorship experiences engender persistence in IT careers.

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