Cognitive and Non-cognitive Predictors of Career Intentions within Cyber Jobs

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Abstract

Building, managing, and retaining a talented and sufficient number of cyber employees has been a challenge within the Federal Government. This research investigates the relationships between cognitive ability, cyber knowledge, job-fit, and normative commitment to predict Army career intentions in two cyber occupations. Findings show that individuals with lower cyber knowledge at the beginning of training report higher Army career intentions at the end of training when their job-fit was high versus when it was low. For individuals high in cyber knowledge/potential, Army career intentions remained the same regardless of the degree of job-fit reported. Implications are discussed.

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14. ABSTRACT

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It has been said that all technology comes with a price. Indeed, with the advent of our vast information system networks that have catapulted mankind into a new technological age and offered promises of prosperity, has come the price of vulnerability on an unfathomable scale. The rise of the cyber field as a point of focus is reflective of the now ubiquitous integration of computers. Those working in the cyber field help harness the awesome power this technology provides while ensuring that vulnerabilities in its integration are mitigated. Cyber warfare incidents are increasing (Goel, 2011), and can be potentially devastating at both the national and commercial level. Although originally a Military issue, information warfare is transitioning into a major commercial issue (Knapp & Boulton, 2006). Recent incidents, including the cyber-attack on the Office of Personnel Management (OPM) and Sony studios, are examples of this inclusion of specific agencies and organizations as targets of cyber warfare.

Despite this increase in frequency and severity of cyber warfare incidents, the Federal Government continues to face a shortage in its cyber security workforce (Davidson, 2015). One reason of this shortage is the unfavorable difference in salary between government and private cyber workers (Halzack, 2014). Increased demand and compensation will bring more people into the cyber field, but it will take time for these people to complete requisite training. Compensation for cyber workers is skewed to those in private industry as well as some non-Department of Defense agencies (e.g., NSA). In an effort to address the cyber workforce shortage, this paper addresses the relationship between key selection measures and cyber career intentions, and presents a model in which these relationships can not only be further understood, but utilized in the pursuit of a stronger cyber security workforce.

The gravitational hypothesis states that individuals tend to sort into jobs that are commensurate with their ability level (McCormick, Jeanneret, & Mecham, 1972). This hypothesis has been supported empirically (Wilk & Sackett, 1996). Given this finding, and given the cognitively demanding nature of cyber occupations, it stems to reason that individuals who are higher in cognitive ability will have higher levels of job-fit in these occupations. Therefore, we hypothesize:

H1: Cognitive ability will positively predict job-fit.

Building a premier cyber workforce has, thus far, presented a challenge for the Federal government (Wilson & Wilson, 2011) for two reasons. First, these positions are difficult to fill because of the high standards for entry. Second, there is a recorded high level of turnover from government cyber jobs in which employees are leaving for the private sector, where job compensation can be markedly higher (Halzack, 2014). Given this finding that cyber employees leave the government sector for private industry and the assumption that individuals higher in cognitive ability will be more attractive to private companies, we predict the following:

H2: Cognitive ability will negatively predict Army career intentions (ACI).

The Armed Services Vocational Aptitude Battery (ASVAB) is a nine section computer-adaptive cognitive test that is used to determine enlistment eligibility and classification. The ASVAB has proven to be a very useful selection aid for Military careers including those in cyber occupations (Drasgow, Embretson, Kyllonen, & Schmitt, 2006), which are cognitively demanding. Individuals with higher levels of cognitive ability are more likely to have the capacity to meet the cognitive demands required by cyber jobs.

H3: Cognitive ability will positively predict cyber knowledge/potential.

Person-job-fit, defined as the compatibility of the individual with the job (Edwards, 1991), is a component of the broader construct person-environment fit, one of the most pervasive constructs in industrial-organizational psychology (Kristof-Brown & Guay, 2011). The majority of studies related to fit assess its relationships with employee attitudes, such as intention to quit (Kristof-Brown & Guay, 2011). For example, a strong negative correlation (rho = -.46) between person-job-fit and intention to quit was identified in a meta-analysis conducted by Kristof-Brown and colleagues (2005). However, some Cyber/I.T. MOS Soldiers see the Army as a beginning to their career, while they obtain their certifications/training, before moving to the private sector for compensation reasons (Cheravitch, 2013; Halzack, 2014), making it likely that higher levels of job-fit will be related to lower levels of career intentions. Individuals for whom job-fit is high are more likely to pursue a career in *cyber* but not necessarily as a Soldier, where compensation amounts are determined by level and not occupation.

H4: Job-fit will negatively predict ACI.

In addition, we propose that individuals who have high job-fit combined with high scores on cyber knowledge potential (CKP) will be even less likely to show high career intentions compared to individuals who score high on job-fit but have lower CKP. In other words, we hypothesize that CKP will moderate the relationship between job-fit and ACI, such that individuals with higher CKP scores will show a stronger (negative) relationship between job-fit and ACI. This is based on the reasoning that individuals with higher knowledge and capabilities will be more attractive to private sector companies (Rausnitz, 2014), and this, combined with a good fit in a cyber-occupation (reflected in their high job-fit scores), will lead them to be more likely to pursue a career outside of the Army.

H5: Job-fit and CKP will interact to predict ACI such that the relationship between job-fit and ACI will be more strongly negative when CKP is higher versus when CKP is lower.

In addition to its relationship with cognitive ability and career intentions, job-fit has been associated with organizational commitment (Kristoff-Brown, 2005). Organizational commitment is composed of three sub-factors: normative commitment, affective commitment, and continuance commitment (Meyer & Allen, 1990). As this paper focuses on a Military sample, it is important to note that normative commitment has been found to be relatively higher in the US Army (Milligan, 2003) as compared to private sector organizations. As normative commitment is a measure of the feeling that one “ought” to stay at, or has a sense of duty toward, an organization (Allen & Meyer, 1990), it appears that, in at least some federal organizations, feelings of duty toward the organization may be relatively higher than in private industry. Given this relative importance of normative commitment in the Military, we have chosen to focus on this variable as a measure of organizational commitment. Based on the prior research supporting strong relationships between person-job-fit and organizational commitment (Kristoff-Brown, 2005), we propose that:

H6: Job-fit will positively predict normative commitment.

The construct of organizational commitment was originally developed as a predictor of turnover and has since been found to improve turnover prediction and explanation. Schleicher, Hansen, and Fox (2011) summarized six meta-analyses that investigated the relationship between organizational commitment and turnover intentions (mean r’s ranging from -.46 to -.47), and two meta-analyses on actual turnover (mean r’s ranging from -.19 to -.25). A conclusion from their study is that organizational commitment is most strongly related to turnover intentions, followed by actual turnover. Given this strong relationship between organizational commitment and turnover, we predict:

H7: Normative commitment will positively predict ACI.

Again drawing from the gravitational hypothesis (McCormick, Jeanneret, & Mecham, 1972), we predict that higher scores on CKP at the beginning of training will be positively related to person-job-fit. Individuals who score high on CKP, and thus have a higher potential for success in the cyber domain, will be those who tend to "gravitate" toward occupations in cyber because they are likely to have better fit with those jobs.

H8: CKP will positively predict job-fit.

Stemming from hypothesis 2, in which cognitive ability is predicted to be negatively related to ACI, we also predict that CKP will be negatively related to ACI. This is also due to the circumstances surrounding the turnover rates, and direction, among government cyber employees, in which many leave and head towards the private sector (Nagesh, 2009). Individuals with higher CKP at the beginning of training will be more likely to leave government organizations, and will therefore be less likely to have high ACI.

H9: CKP will negatively predict ACI.

Method

Participants

Of the original sample size of 2,143 Information Technology Specialists[1] and Nodal Network Operator Maintainers[2] from the Army, cases were excluded using list-wise deletion due to much missing data (most of the deleted cases had over half the variables missing), resulting in a final sample size of N=1,119. There were 976 (87.2%) Information Technology Specialists and 143 (12.8%) Nodal Network Operator Maintainers. The average education level (M=3.60, SD=0.96) was between high school diploma and college Bachelor's degree. The average self-reported Army Physical Fitness Test (APFT) score was M=231.42 (SD=38.77).

Measures

Cyber knowledge/potential. The Information Communication Technology Literacy (ICTL) test is a 29 item computer-based assessment covering four Cyber content areas: I.T. software/tools and PC configuration/maintenance, Security and compliance, Networking and communications, and Software programming and web development. Scaled Item Response Theory ICTL scores range between 1 and 79. The ICTL was administered at the beginning of job training.

Cognitive ability. Four of the Armed Services Vocational Aptitude Battery (ASVAB) tests (Mathematics Reasoning, Arithmetic Knowledge, Paragraph Comprehension, and Word Knowledge) are combined into a composite known as the Armed Forces Qualification Test (AFQT), which is used to determine enlistment eligibility in the Department of Defense. AFQT scores function as a measure of cognitive ability. Cognitive ability was assessed prior to joining the Army.

Army Life Questionnaire (ALQ). Self-report measures of affective commitment, normative commitment, Army life adjustment, Army fit, career intentions, reenlistment intentions, and Military

[1] MOS 25B- Information technology specialists are responsible for maintaining, processing and troubleshooting military computer systems/operations (goarmy.com).
[2] MOS 25N- The nodal network systems operator-maintainer is responsible for making sure that the lines of communication are always up and running. They maintain strategic and tactical nodal systems (goarmy.com).

Occupational Specialty (MOS) fit were used. The ALQ was administered at the end of job training. The specifics of these measures are listed in Table 1.

Procedure

Cyber knowledge/potential scores were pulled from administrative records for all Soldiers who voluntarily completed the online version of the Army Life Questionnaire. The questionnaire took approximately 20 minutes to complete. Soldiers were not compensated beyond their hourly salaries for their participation.

Results

Descriptive statistics for the whole sample are displayed in Table 2. The sample (N=1,119) was randomly split into a calibration sample (N=560) and a cross-validation sample (N=559) using SPSS 21. Results were analyzed using AMOS 21 and Kenny's (2015a) path analysis steps. The hypothesized model (see Figure 2 and Table 3) had very good fit using the calibration sample, $\chi^2(6)=8.90$, $p=.179$, CFI=.993, RMSEA=.029. Kenny (2015a) recommends testing deleted paths as a second step and using a reduced alpha level (e.g., .01) as a criterion for retention. Paths from CKT to normative commitment ($\beta=-.11$, $p=.026$) and cognitive ability to ACI ($\beta=.05$, $p=.267$) were added. While this improved model fit, $\chi^2(4)=3.94$, $p=.414$, CFI=1.000, RMSEA=.000 (see Figure 3 and Table 4), these paths were not retained since they failed to meet the reduced alpha level. Non-significant paths were not trimmed since the model was to be cross-validated (Kenny, 2015a).

Cross-Validation

The cross validation of the trimmed model was run on the cross validation sample (N=559). The initial fit of the trimmed model using this holdout sample was acceptable, $\chi^2(6)=18.533$, $p=.005$, CFI=.975, RMSEA=.061 (see Figure 4 and Table 5). The base configural (unconstrained) model had reasonable fit (see Table 6), $\chi^2(12) = 27.434$, $p=.007$, CFI = .983, RMSEA = .034. Hence, it was reasonable to proceed with testing a progressive series of nested models, each of which adds an additional constraint to the model, while retaining all model constraints from previous steps (Kenny, 2015b).

Each constraint added to the model forced certain model parameters within the calibration and cross-validation sample to be equal. The constraints tested included (in order) structural weights, structural covariances, and structural residuals. According to Kenny (2015b), it is most appropriate to look for changes in fit using a fit index other than the chi square difference test, such as the CFI or RMSEA. The results of the test of these nested models appears in Table 6.

As can be seen in Table 6, the addition of each additional constraint results either in no difference in fit (invariance) or a very slight improvement of the fit right up through model III, in which structural residuals were constrained to be equal (CFI = .984, RMSEA = .022). Conclusively, no model differences were found between the calibration and cross-validation samples. Thus, model III (see Figure 5 and Table 7) were used to test the hypotheses.

Tests of Hypotheses

Hypothesis 1 was not supported in that cognitive ability did not predict job-fit, $\beta=.014$, $p=.698$.

Hypothesis 2 was supported such that cognitively ability negatively predicted ACI, $\beta=-.157$, $p<.001$.

Hypothesis 3 was supported such that cognitive ability positively predicted CKP, $\beta=.555$, $p<.001$.

Hypothesis 4 was not supported in that job-fit did not directly predict ACI, $\beta=.013$, $p=.649$. However, this is not surprising, given that the job-fit x CKP interaction was statistically significant, $\beta=-.090$, $p<.001$. A plot of the interaction (see Figure 6) shows that for Soldiers with high CKP, ACI was not impacted by whether Soldiers reported low job-fit or high job-fit. However, for Soldiers with low CKP, Soldiers reporting high job-fit also expressed stronger Army career intentions as compared to Soldiers reporting low job-fit. This partially supports Hypothesis 5.

Job-fit positively predicted normative commitment, $\beta=.273$, $p<.001$, thus supporting Hypothesis 6. In turn, normative commitment positively and strongly predicted ACI, $\beta=.474$, $p<.001$, thus supporting Hypothesis 7.

Hypothesis 8 was supported such that CKP positively predicted job-fit, $\beta=.235$, $p<.001$. Finally, Hypothesis 9 was supported in that CKP negatively predicted ACI, $\beta=-.082$, $p=.010$.

Discussion

This paper attempted to build a model to explain the relationships between cognitive ability, cyber potential, job-fit, and normative commitment on the outcome of army career intentions in a cyber-workforce sample. The most important findings in the model demonstrate the complexity of the relationship between job-fit and ACI. Even though the direct relationship was near zero, Soldiers with low CKP at the beginning of training reported higher ACI at the end of training when their perceived job-fit was higher versus lower. The level of job-fit did not affect the ACI of Soldiers with high CKP. It is common that some cyber/I.T. Soldiers see the Army as a beginning to their career, while they obtain their certifications/training before moving to the private sector for better compensation (Cheravitch, 2013; Halzack, 2014). It is possible that Soldiers with higher CKP scores are more likely to seek opportunities outside of the Army regardless of their job-fit.

Furthermore, another potential benefit of the model is that by increasing job-fit, this leads to higher normative commitment, which in turn, leads to higher ACI. However, it cannot be concluded that the relationships between these variables are causative and necessarily flow in this direction, and therefore future research should address this limitation. The data suggest that when Soldiers experience a high level of job-fit, they become more obligated to the Army for providing them with a good fitting job, which increases their normative commitment, which, in turn, makes it more likely Soldiers will continue their career in the Army since they feel more of an obligation to remain with the Army. This finding is similar to Morgan's (2015) hypothesis that higher levels of company similarity will positively predict normative commitment. By adding a measure of normative commitment to selection batteries, government agencies may be able to avoid the loss of their cyber workers highest in potential by focusing on bringing in those with higher normative commitment, which are more likely to pursue a career with the organization. McCullough and Turban's (2007) study highlights the feasibility of adding such a measure, in that their added person-organization fit measure when added to an assessment battery added significant validity in predicting employee retention in a sample of call center agents.

Other implications of these findings include the importance of organizations taking actions that may increase the normative commitment of their employees. Future research may examine if specific types of Army policies and rewards have any effect on enhancing normative commitment. For example, desire for a Military career and mental toughness predicted normative commitment within a Canadian Military sample (Godlewski & Kline, 2012). Future research may verify if these results generalize to the U.S. Army. The Army can either select for these characteristics or promote development of them in new recruits through sponsored activities to increase normative commitment.

Previous research has found that Soldiers higher in cognitive ability tend are less likely to consider breaking their enlistment contracts, but are more likely to plan to leave at the end of their enlistment term (Knapp, Tremble, Russell & Sellman, 2008). This research is consistent with that finding, but it also demonstrates that the effect is amplified within the cyber domain.

The limitations of the current research are that the data were collected as part of a cross-sectional design (Uematsu, Mishra, & Powell, 2012). Also, findings were based on a military sample, which may raise questions about other settings to which the results may apply. Future research may focus on whether findings generalize to other settings even within the Federal government.

Future research may also focus on other predictors of normative commitment or possibly on moderators that may help to strengthen the normative commitment – career intentions relationship. Similarly, finding moderators that weaken the negative relationship between cognitive ability and ACI would also be most valuable, such as possible rewards, recognition, or financial incentives.

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Table 1. Army Life Questionnaire Measures.

Scale Name	Number of Items	Example Item	Likert Scale Anchors
Military Occupational Specialty (MOS) Fit	6	My MOS provides the right amount of challenge for me.	1 (strongly disagree) to 5 (strongly agree)
Army Career Intentions	3	How likely is it that you will make the Army a career?	Varies by item: 1 (strongly disagree) to 5 (strongly agree); 1 (not at all confident) to 5 (extremely confident); 1 (extremely unlikely) to 5 (extremely likely)
Normative Commitment	5	I would feel guilty if I left the Army before the end of my current term of service.	1 (strongly disagree) to 5 (strongly agree)

Note: All Cronbach's Alpha reliabilities were at least in the acceptable range of being greater than .70.

Table 2. Descriptive statistics and correlations among the model variables. (N = 926)

	Mean	**SD**	**1**	**2**	**3**	**4**	**5**
1. Cyber Knowledge / Potential	56.55	8.14	1				
2. Job-fit	3.82	0.78	.243**	1			
3. Army Career Intentions	3.06	1.07	-.176**	.098**	1		
4. Normative Commitment	4.04	0.71	-.006	.273**	.467**	1	
5. Cognitive Ability (AFQT)	65.67	16.55	.555**	.144**	-.179**	.057	1

Table 3.

Hypothesized model path coefficients using the calibration sample (N = 560).

Paths			Stnd. Estimate	S.E.	C.R.	P
Cognitive Ability	→	Job-fit	.013	.002	-0.272	.786
Cognitive Ability	→	Army Career Intentions	-.145	.003	-3.336	<.001
Cognitive Ability	→	Cyber knowledge / potential	.546	.017	15.425	<.001
Job-fit	→	Army Career Intentions	.036	.052	0.942	.346
Job-fit x Cyber Knowledge / Potential Interaction	→	Army Career Intentions	-.122	.006	-3.351	<.001
Job-fit	→	Normative Commitment	.237	.038	5.775	<.001
Normative Commitment	→	Army Career Intentions	.441	.055	11.710	<.001
Cyber Knowledge / Potential	→	Job-fit	.236	.005	4.798	< .001
Cyber Knowledge / Potential	→	Army Career Intentions	-.116	.006	-2.595	.009

Table 4.

Test of deleted paths, calibration sample (N = 560).

Paths			Stnd. Estimate	*S.E.*	*C.R.*	*P*
Cognitive Ability	→	Job-fit	-.013	.002	-0.272	.786
Cognitive Ability	→	Army Career Intentions	-.145	.003	-3.336	<.001
Cognitive Ability	→	Cyber knowledge / potential	.546	.017	15.425	<.001
Job-fit	→	Army Career Intentions	.036	.052	.942	.346
Job-fit x Cyber Knowledge / Potential Interaction	→	Army Career Intentions	-.122	.006	-3.351	<.001
Job-fit	→	Normative Commitment	.256	.039	6.102	<.001
Normative Commitment	→	Army Career Intentions	.439	.055	11.710	<.001
Cyber Knowledge / Potential	→	Job-fit	.236	.005	4.798	< .001
Cyber Knowledge / Potential	→	Army Career Intentions	-.115	.006	-2.595	.009
Cyber Knowledge / Potential	→	Normative Commitment	-.111	.004	-2.230	.026
Cognitive Ability	→	Normative Commitment	.054	.002	1.109	.267

Table 5.

Test of the model using the cross-validation sample (N =559).

Path			Stnd. Estimate	*S.E.*	*C.R.*	*P*
Cognitive Ability	→	Job-fit	.042	.002	0.841	.400
Cognitive Ability	→	Army Career Intentions	-.169	.003	-3.890	<.001
Cognitive Ability	→	Cyber knowledge / potential	.564	.017	16.114	<.001
Job-fit	→	Army Career Intentions	-.015	.054	-0.394	.694
Job-fit x Cyber Knowledge / Potential Interaction	→	Army Career Intentions	-.062	.007	-1.707	.088
Job-fit	→	Normative Commitment	.310	.036	7.696	<.001
Normative Commitment	→	Army Career Intentions	.510	.059	13.467	<.001
Cyber Knowledge / Potential	→	Job-fit	.234	.005	4.721	< .001
Cyber Knowledge / Potential	→	Army Career Intentions	-.048	.006	-1.077	.281

Table 6.

Cross validation of the trimmed model.

Model	***Tested***	***Chi Square***	***df***	***CFI***	***RMSEA***	***Chi Square Difference Test***
	Unconstrained Model	27.43	12	.983	.034	
I	Structural Weights	35.56	21	.984	.025	$\Delta\chi^2(9) = 8.124$, $p = .521$
II	Structural Covariances	37.808	23	.984	.024	$\Delta\chi^2(2) = 2.247$, $p = .325$
III	Structural Residuals	41.885	27	.984	.022	$\Delta\chi^2(4) = 4.077$, $p = .396$

Table 7.

Best fitting cross-validation model used to test the hypotheses.

	Path		Stnd. Estimate	*S.E.*	*C.R.*	*P*
Cognitive Ability	→	Job-fit	.014	.002	0.388	.698
Cognitive Ability	→	Army Career Intentions	-.157	.002	-5.087	<.001
Cognitive Ability	→	Cyber knowledge / potential	.555	.012	22.272	<.001
Job-fit	→	Army Career Intentions	.013	.038	.456	.649
Job-fit x Cyber Knowledge / Potential Interaction	→	Army Career Intentions	-.090	.005	-3.503	<.001
Job-fit	→	Normative Commitment	.273	.026	9.488	<.001
Normative Commitment	→	Army Career Intentions	.474	.040	17.746	<.001
Cyber Knowledge / Potential	→	Job-fit	.235	.003	6.737	< .001
Cyber Knowledge / Potential	→	Army Career Intentions	-.082	.004	-2.587	.010

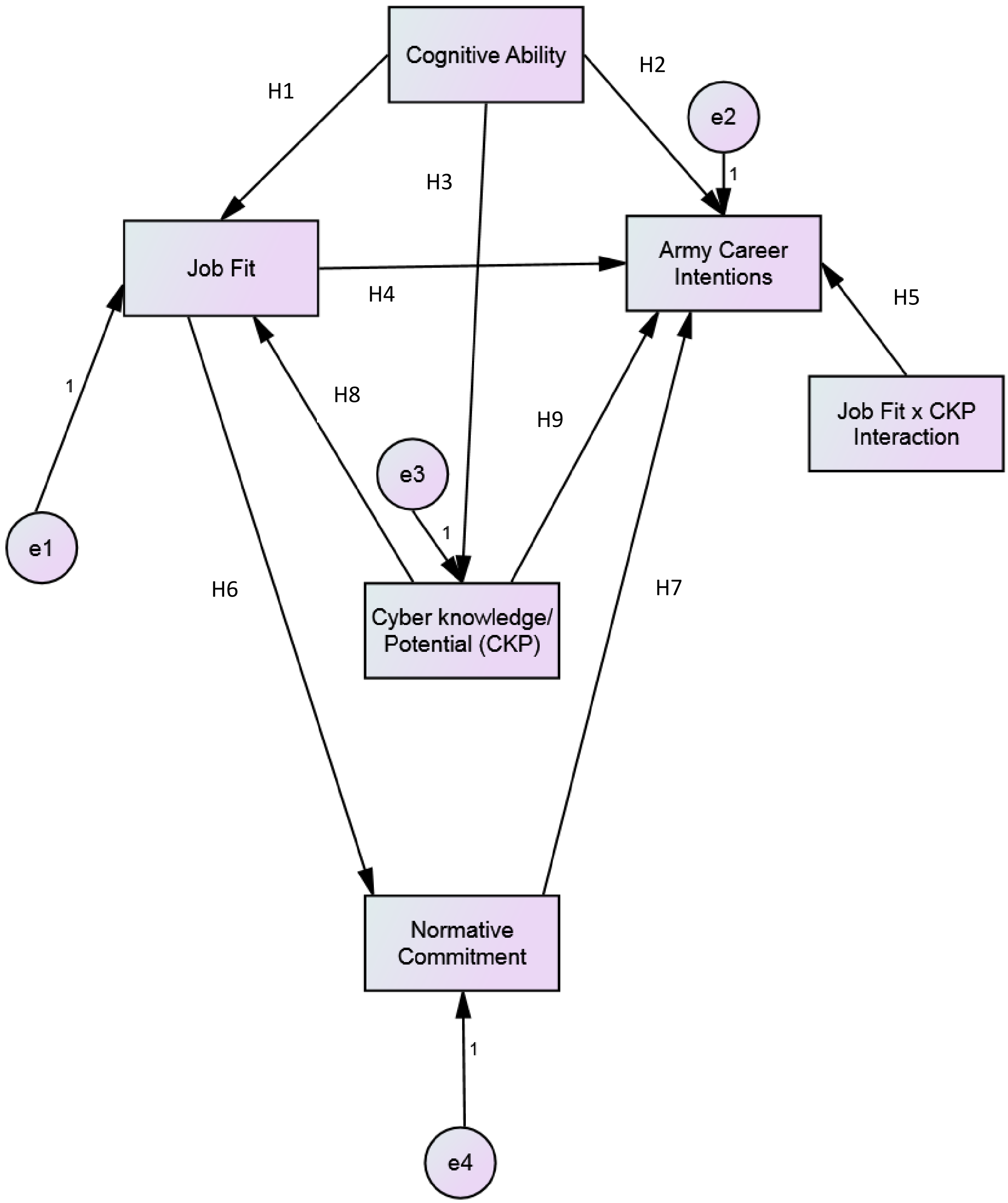

Figure 1. Hypothesized model.

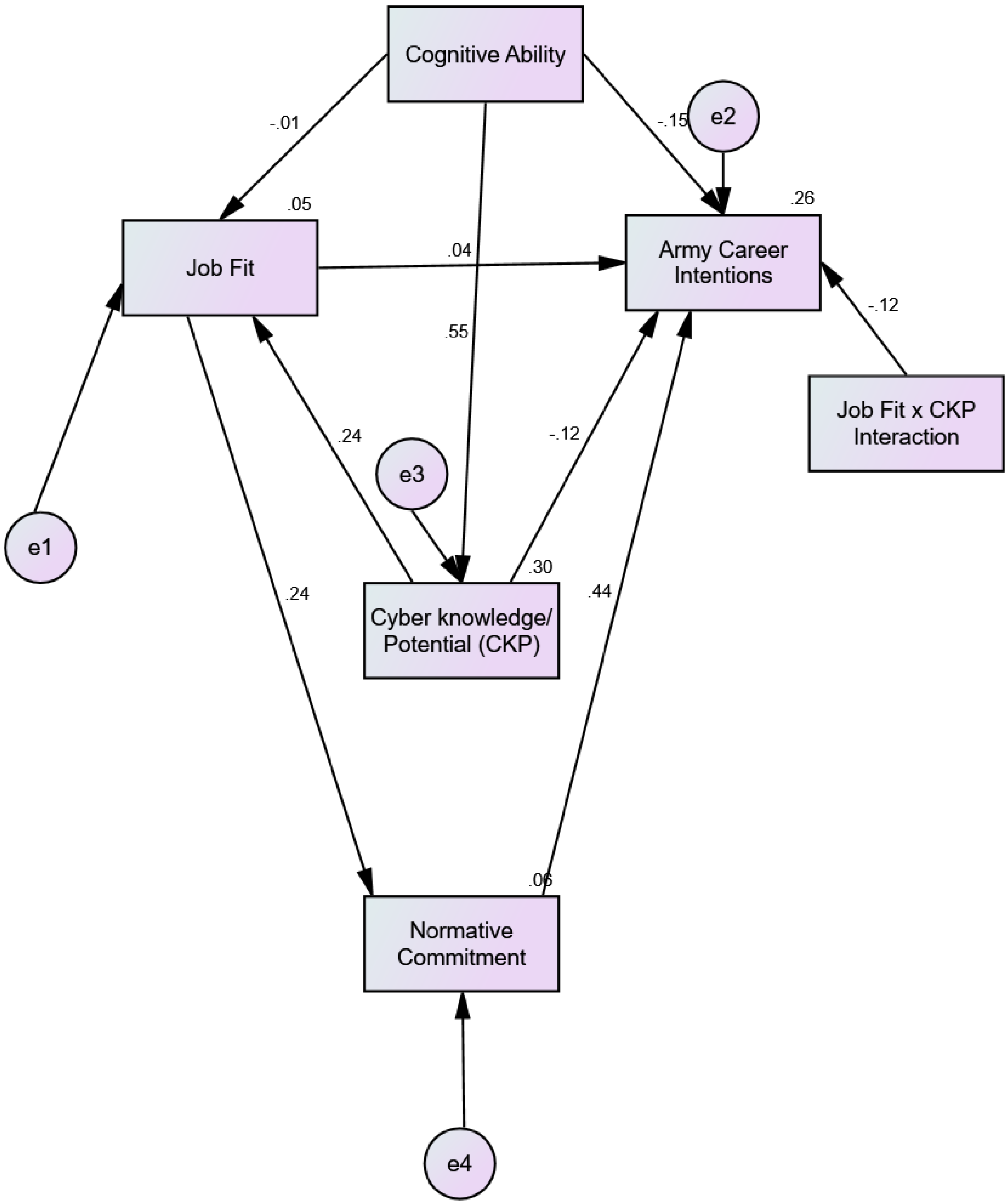

Figure 2. Test of hypothesized model, $\chi^2(6)=8.90$, $p=.179$, CFI=.993, RMSEA=.029.

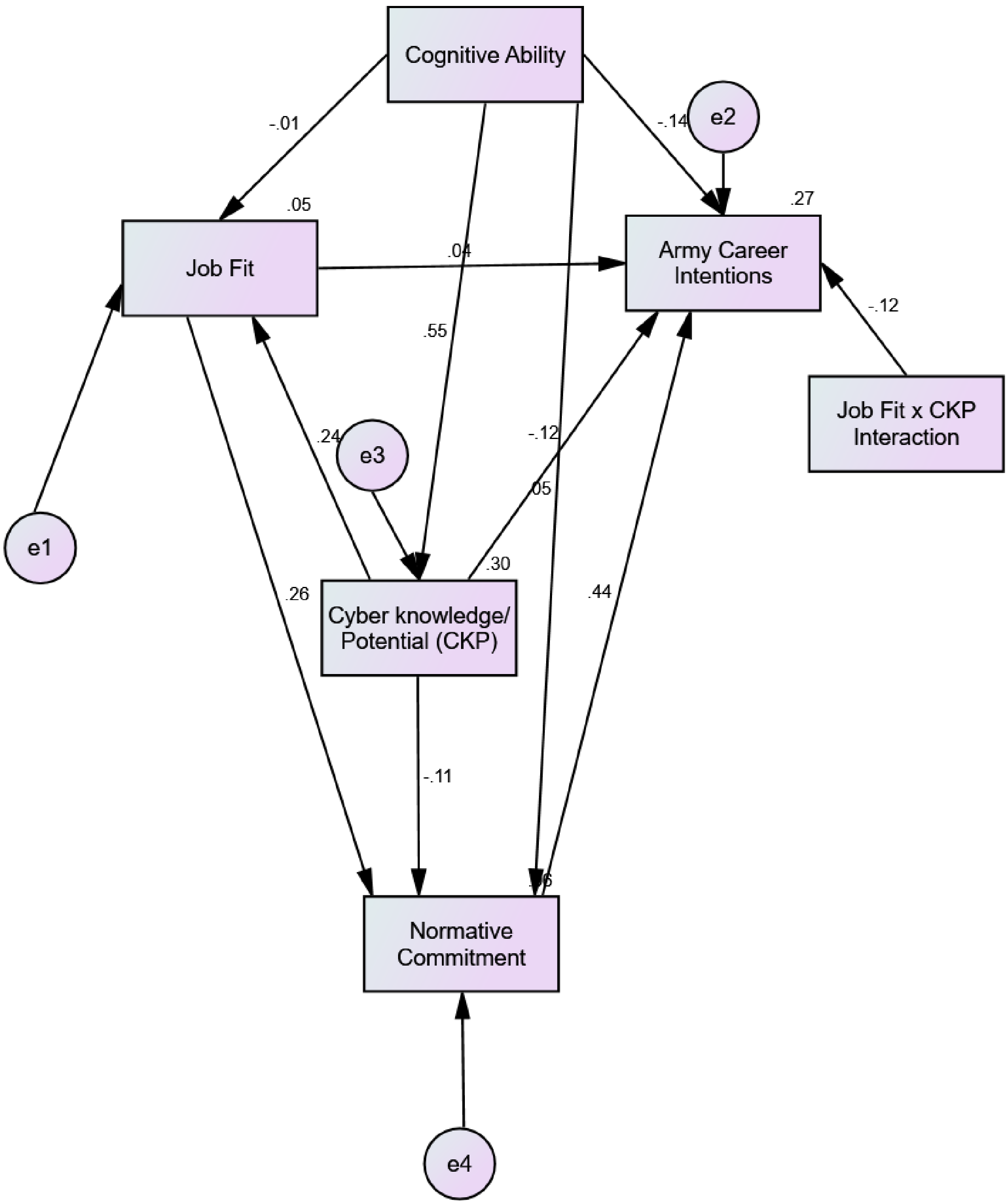

Figure 3. Test of deleted paths, $\chi^2(4) = 3.94$, $p = .414$, CFI = 1.000, RMSEA = .000.

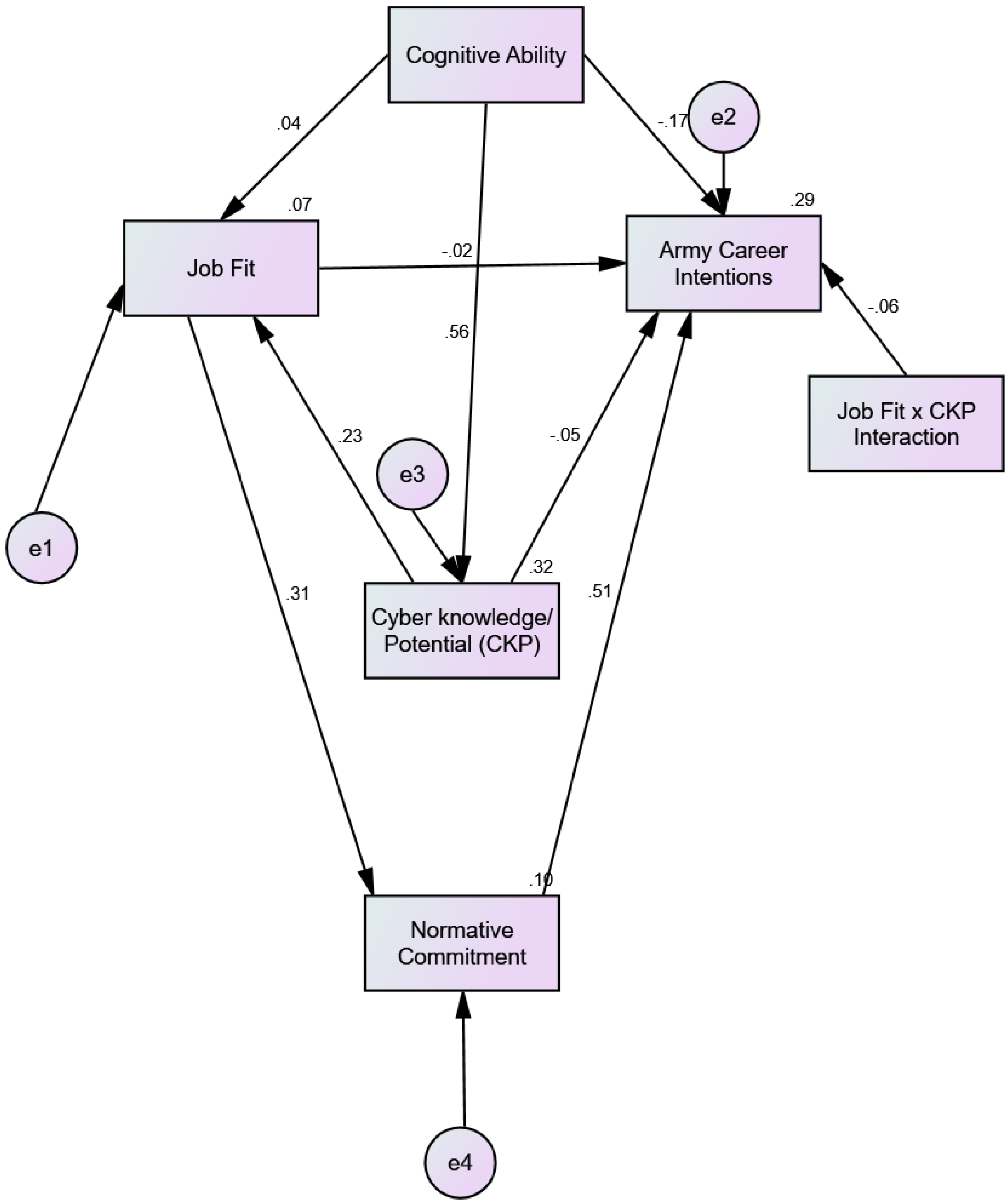

Figure 4, Model tested with the cross-validation sample, $\chi^2(6) = 18.533$, p=.005, CFI = .975, RMSEA = .061.

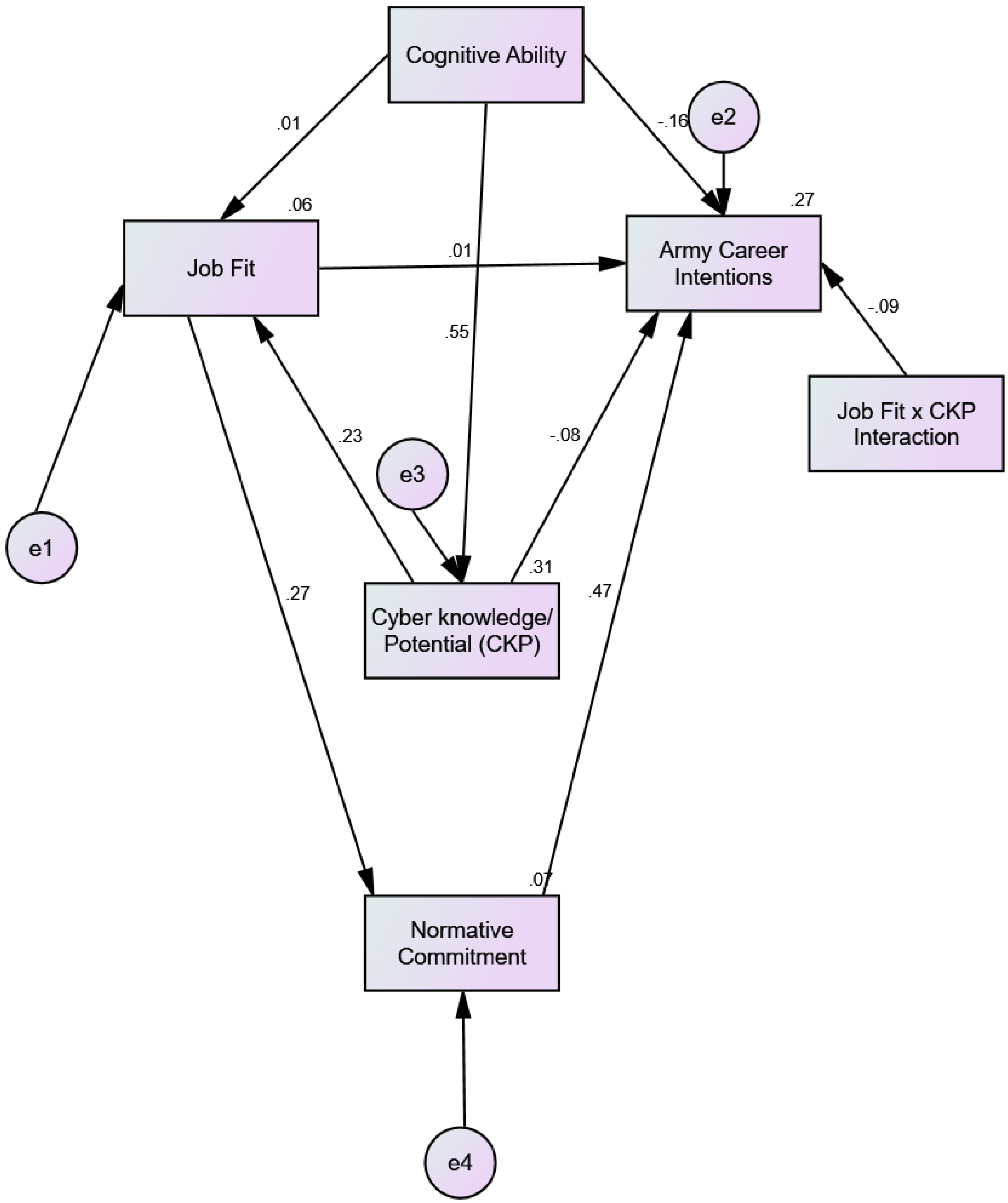

Figure 5. Best fitting, cross-validated model used to test hypotheses, $\chi^2(27) = 41.885$, $p=.034$, CFI = .984, RMSEA = .022.

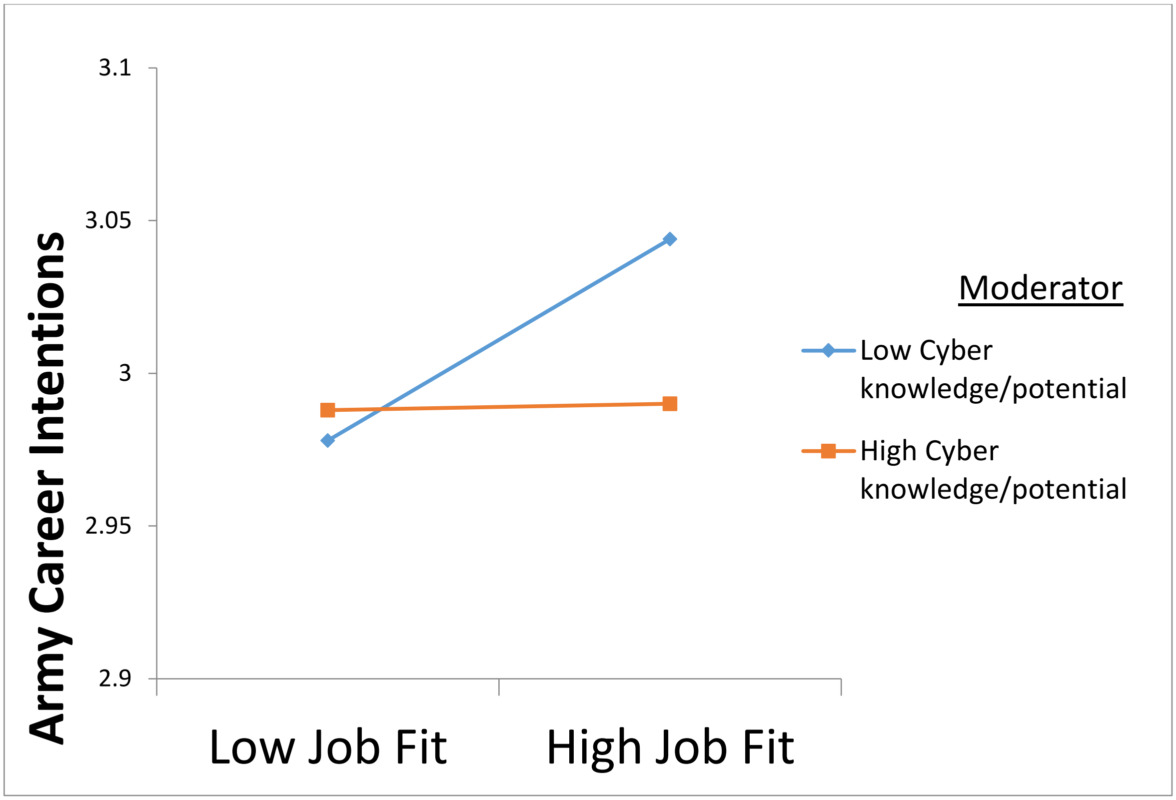

Figure 6. CKT as a moderator of the relationship between job-fit and ACI.

Abstract

Information Technology Specialists and Nodal Network Operator Maintainer Soldiers participated in research that examines how cognitive ability, cyber knowledge, job-fit, and normative commitment predict Army career intentions (ACI). Findings include an interaction between cyber knowledge test scores and job-fit in predicting Army career intentions. Implications are discussed.

Introduction

- Cyber warfare incidents are increasing and can be potentially devastating
- Information warfare is transitioning into a major commercial issue
- Federal Government continues to face a shortage in its cyber security workforce
  - Difference in salary of government and private cyber workers is contributing factor
- Person-job-fit, compatibility of the individual with the job, is component of the broader person-environment fit, one of the most pervasive constructs in industrial-organizational psychology
- Individuals for whom job-fit is high are more likely to pursue a career in *cyber* but not necessarily in the government
- Hypothesize cyber knowledge/potential (CKP) will moderate the relationship between job-fit and ACI, such that individuals with higher CKP scores will show a stronger (negative) relationship between job-fit and ACI
  - Individuals with higher CKP scores will be more attractive to private sector companies
- Job-fit has been associated with organizational commitment
- As normative commitment is a measure of the feeling that one "ought" to stay, we propose that: job-fit will positively predict normative commitment, which will predict ACI in turn

The views, opinions, and findings expressed here are solely those of the authors and do not purport to represent the views of the U.S. Army Research Institute for the Behavioral and Social Sciences or George Mason University. They should not be construed as an official U.S. Department of the Army or U.S. Department of Defense position, policy, or decision, unless so designated by other documentation.

Theoretical Model

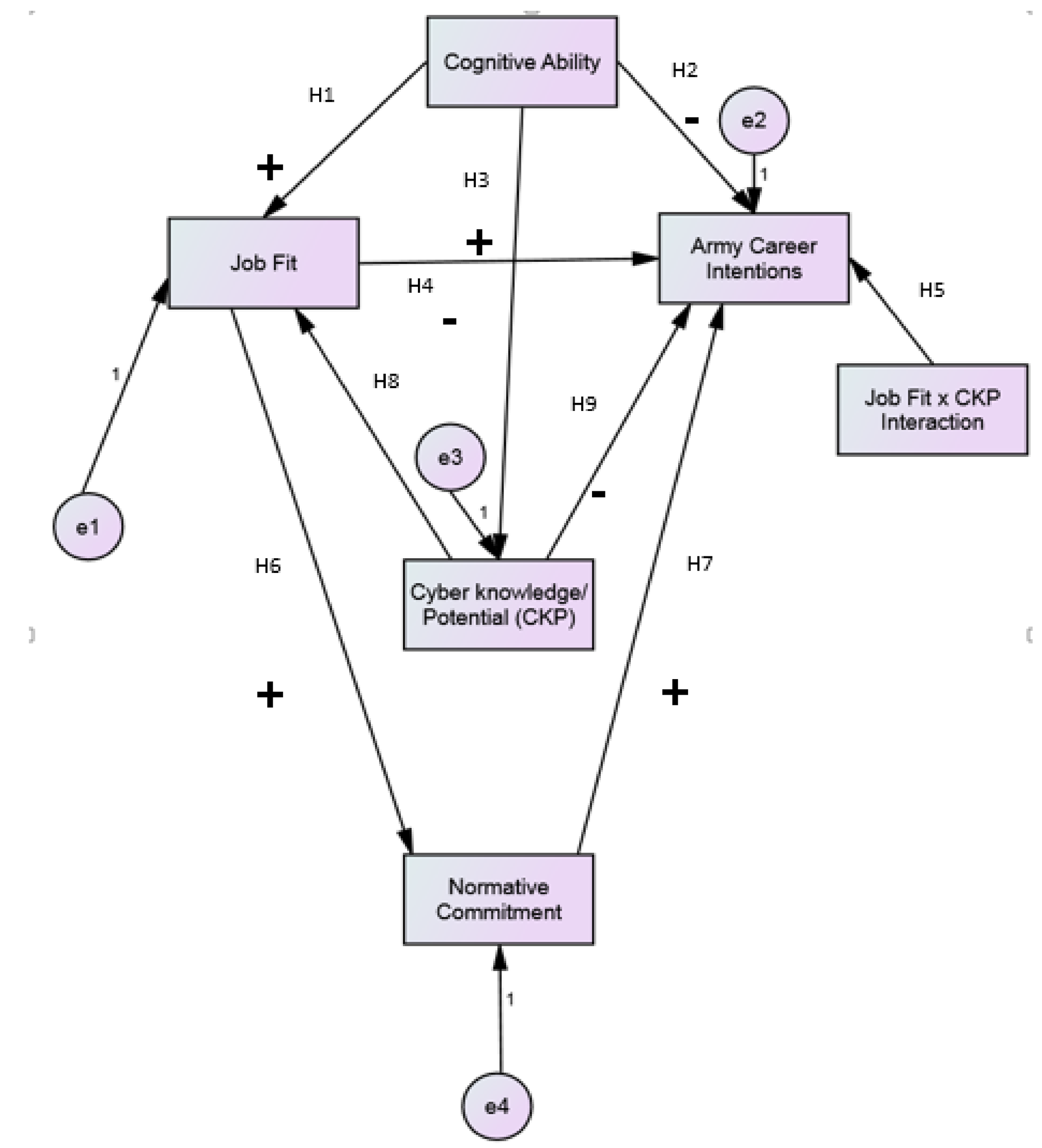

Figure 1. Hypothesized model.

Participants

- Original sample of 2,143 I.T. Specialists and Nodal Network Operator Maintainers from the U.S. Army, cases were excluded using list-wise deletion for missing data, resulting in final sample N=1,119
  - 976 (87.2%) Information Technology Specialists
  - 143 (12.8%) Nodal Network Operator Maintainers

Measures

Table 1. Measures.

Scale Name	Number of Items	Example Item	Likert Scale Anchors
Military Occupational Specialty (MOS) Fit	6	My MOS provides the right amount of challenge for me.	1 (strongly disagree) to 5 (strongly agree)
Army Career Intentions	3	How likely is it that you will make the Army a career?	Varies by item: 1 (strongly disagree) to 5 (strongly agree); 1 (not at all confident) to 5 (extremely confident); 1 (extremely unlikely) to 5 (extremely likely)
Normative Commitment	5	I would feel guilty if I left the Army before the end of my current term of service.	1 (strongly disagree) to 5 (strongly agree)
Cyber Knowledge/ Potential Test	29		Scores range from 1-79
Armed Forces Qualification Test		Four of the Armed Services Vocational Aptitude Battery (ASVAB) tests (Mathematics Reasoning, Arithmetic Knowledge, Paragraph Comprehension, and Word Knowledge) were combined into a composite.	

Note: All Cronbach's Alpha reliabilities were at least in the acceptable range of being greater than .70.

Results

Table 2. Descriptive statistics and correlations among the model variables. (N = 926)

	Mean	SD	1	2	3	4	5
1. Cyber Knowledge / Potential	56.55	8.14	1				
2. Job-fit	3.82	0.78	.243**	1			
3. Army Career Intentions	3.06	1.07	-.176**	.098**	1		
4. Normative Commitment	4.04	0.71	-.006	.273**	.467**	1	
5. Cognitive Ability (AFQT)	65.67	16.55	.555**	.144**	-.179**	.057	1

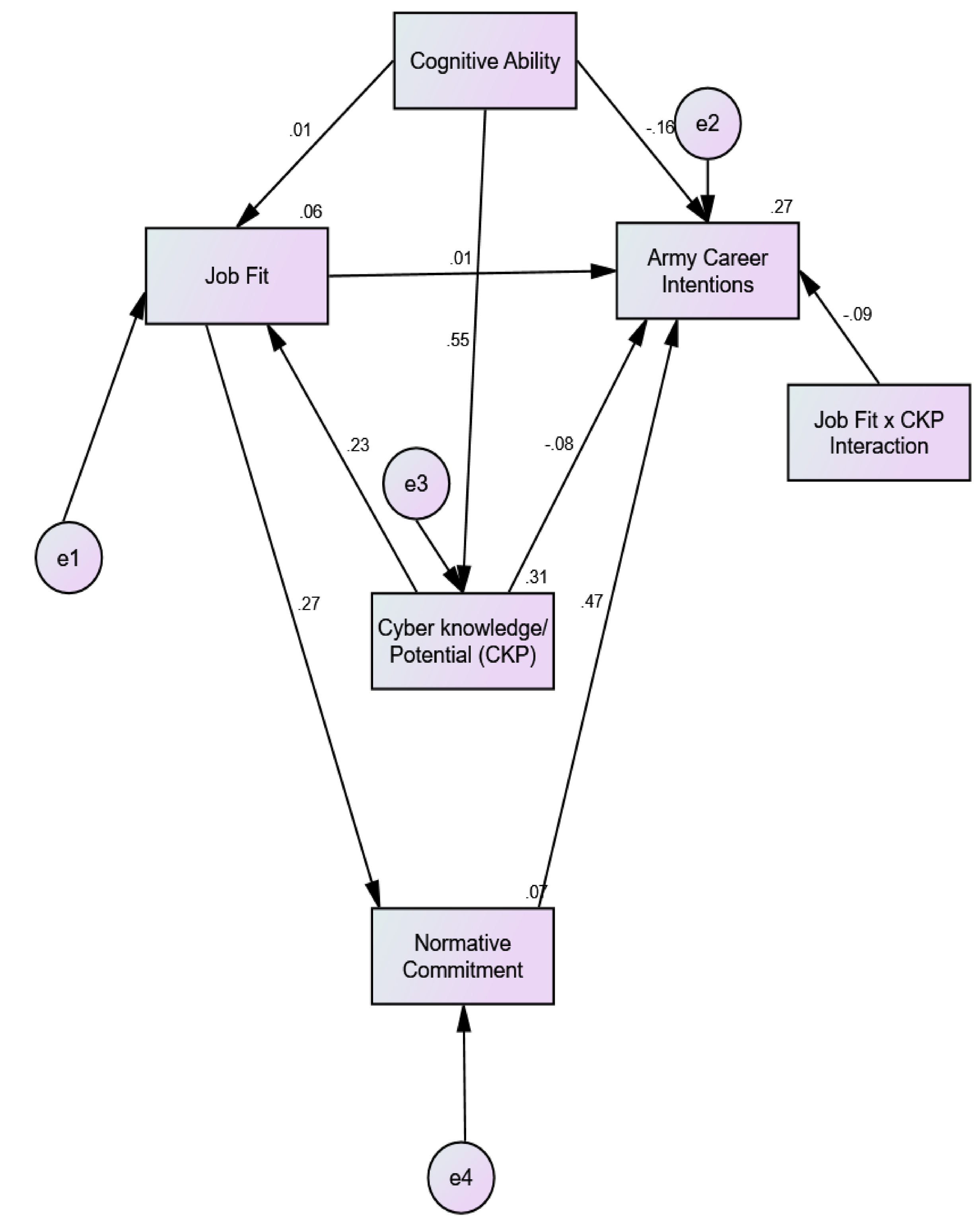

Figure 2. Best fitting, cross-validated model used to test hypotheses, $\chi^2(27) = 41.885$, p=.034, CFI = .984, RMSEA = .022

Table 3. Cross validation of the trimmed model.

Model	*Tested*	*Chi Square*	*df*	*CFI*	*RMSEA*	*Chi Square Difference Test*
	Unconstrained Model	27.43	12	.983	.034	
I	Structural Weights	35.56	21	.984	.025	$\Delta\chi^2(9) = 8.124$, p = .521
II	Structural Covariances	37.808	23	.984	.024	$\Delta\chi^2(2) = 2.247$, p = .325
III	Structural Residuals	41.885	27	.984	.022	$\Delta\chi^2(4) = 4.077$, p = .396

- Sample was randomly split into a calibration sample (N = 560) and a cross-validation sample (N = 559)
- Results were analyzed using AMOS 21 and Kenny's (2015) path analysis steps
- For the cross-validation, constraints added in order include structural weights, structural covariances, and structural residuals (see Table 2)

Res

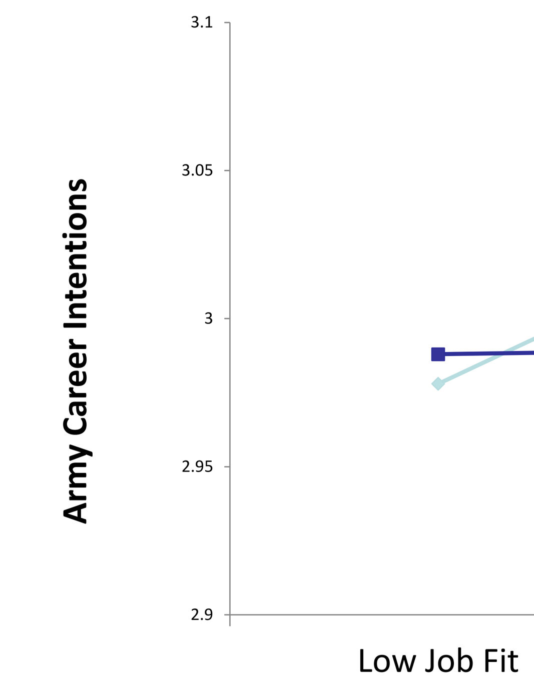

Figure 3. CKT as a
job-fit and ACI.

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