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Predicting Automation of Professional Jobs in Healthcare

Dr. Scott E. Sampson
Marriott School of Business, Brigham Young University
niftyware+hicss@gmail.com

Abstract

Highly-skilled professional jobs have been considered somewhat resistant to automation due to their reliance on judgement and creativity. Still, recent technological advancements such as artificial intelligence are threatening to disrupt even the jobs of professionals. This is particularly relevant in healthcare which accounts for one quarter of all professional jobs in the U.S.

We test a model for predicting job automation based on concepts from recent research literature and extensive U.S. job data. We demonstrate that low automation of professional jobs can be attributed to creative skill requirements and interpersonal skill requirements. When we repeat the analysis with just the healthcare jobs we find that professional training seems to relate to lower amounts of job automation independent from creative and interpersonal skill requirements. Healthcare professions seem resistant to automation beyond what a factor model would explain. We provide theories for the unusually low automation of the jobs of healthcare professionals.

1. Introduction

Automation impacts different jobs and tasks in different ways. Routine tasks are highly susceptible to automation. The threat to repetitive U.S. manufacturing jobs has shifted from offshoring of jobs to automation. As manufacturing productivity increases due to robotics and other technologies, employment shifts from highly-efficient product industries to less-efficient service occupations, which was predicted decades ago by the Clark-Fisher Hypothesis [1]. Service jobs were somewhat protected from technological disruption by the inefficiencies and intricacies of customer interaction.

However, in the past few decades service jobs have become increasingly disrupted by automation [2]. Service employment has decimated jobs such as telephone operators (down 90% from 2001 to 2017), telemarketers (down 61%), survey researchers (down 51%), medical transcriptionists (down 47%), and travel agents (down 45%) [3].

Healthcare fits in the category of so-called "professional" services that have been considered immune from automation. The thought was that professional services are nonroutine and require expert judgment that does not lend itself to automation [4]. Of course, this is a gross overgeneralization, since much of what takes place in healthcare is in fact routine. Further, Artificial Intelligence (AI) technologies have made tremendous inroads in recent years in addressing complex problems that are far from routine [5].

In this exploratory research we analyze automation in healthcare jobs to (a) see if healthcare jobs involving professional training are indeed less susceptible to automation than less-trained healthcare jobs, (b) analyze factors that may inhibit healthcare job automation, and (c) explore how these factors relate to professional training. The overarching research question is whether we can explain observed automation in healthcare professions, and from that whether we can surmise what the future of automation may be in healthcare professions.

In the next section we review some literature about automation of professional jobs, leading to hypotheses about barriers to automation. We test the model using job data compiled by the U.S. Department of Labor. First, we study a set of jobs that spans the U.S. economy, then second, we see if the model holds true for a subset of healthcare jobs. A discussion section explains a distinctive phenomenon occurring in healthcare professions. A final section draws general conclusions.

2. Literature about Professional Automation

In recent years, there has been a gradual increase in research about job automation. Much of the research focuses on how automation will disrupt various industries. Frey and Osborn [6] estimate that 47 percent of jobs in the U.S. are at high risk of being automated away. Chui, et al, [7, p. 5] provide a more

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optimistic forecast, suggesting that only five percent of jobs are at risk of being automated away in the near future. However, they also assert that 60 percent of jobs are likely to have 30 percent or more of their constituent tasks automated away.

As mentioned, in the past it was assumed that professional jobs were immune to automation, or at least resistant to automation. AI may potentially change that. Davenport and Kalakota [8] assert that various forms of AI have immediate relevance in healthcare, including machine learning, natural language processing, expert systems, and even physical robots. This has major implications for technology forecasting, since AI is allowing automation of jobs that are clearly nonroutine. This leads to questions about the potential for job disruption, such as reducing the significant wage gap between professionals and semi-professionals [9].

As stated in the introduction, we are not just interested in whether professional jobs are resistant or susceptible to automation, but also why, which might be explained by distinctive job characteristics. Prior research reveals job and task characteristics that are barriers to automation. Autor [10] suggests that tasks are difficult to automate if they involve (a) creative problem solving, (b) interpersonal ability, and/or (c) physical adaptability. Similarly, Frey and Osborn [6] describe “bottlenecks to automation” including requirements for (a) creative intelligence, (b) social intelligence, and (c) physical perception and manipulation.

Hung and Rust [11] characterize resistance to automation by (a) intuitive intelligence (which they define as the ability to think creatively) and (b) empathetic intelligence (an interpersonal skill). However, they categorize physical tasks as a form of “mechanical intelligence” that they say is more easily automated. Thus, Hung and Rust contradict prior research by asserting that physical acuity is not a barrier to automation.

Thus, we will consider two job requirements that are potential barriers to automation: interpersonal skills and creative skills. There is contradictory theory (and contradictory empirical evidence) about the influence of physical requirements on automation and thus we will defer that topic to future discussion.

An additional question is whether highly-trained professionals have greater resistance to automation than jobs in general. Researchers have suggested that creative expertise is a characteristic that is somewhat distinctive of highly trained professionals [4]. Interpersonal expertise (including empathy) is recognized as being distinctive of professionals, but also may be distinctive of less-trained paraprofessionals [11].

We can represent these concepts in the following hypotheses about job automation:

H1a: Jobs that require **creative skills** are less likely to be automated than jobs in general.

H1b: Jobs that require **interpersonal skills** are less likely to be automated than jobs in general.

H1c: Professional jobs that require **advanced training** are less likely to be automated than jobs in general.

First, we will test these hypotheses for a representation of all jobs in the U.S., then test specifically on healthcare jobs.

3. Test of Hypotheses

We test these hypotheses using empirical data commissioned by the U.S. Department of Labor. The data is called O*Net. Details about the O*Net data are provided by [12] and [13]. The O*Net data has been collected since 1998 at a cost of about $6.5 million per year [14]. The August 2018 O*Net database contains detailed information about 966 jobs, 104 of which are in healthcare occupations. O*Net data covers topics such as worker characteristics, worker requirements, occupational requirements, experience requirements, occupation characteristics, and occupation-specific requirements. Some O*Net data comes from career experts, but most comes from extensive surveys of individuals who have experience in specific jobs.

To test our hypotheses we will need the following job characteristic measurements:

1. Job automation
2. Creative skill requirement
3. Interpersonal skill requirement
4. Professionalism

The following are descriptions of O*Net data items that represent each of these measurements. O*Net data covers much breath of job characteristics but not much depth on any one characteristic.

Job automation. There is no O*Net data about work being susceptible to automation. However, the O*Net Work Context data file contains a Degree of Automation item that measures how automated each job is perceived at currently being. We assume that jobs are automated when they are susceptible to automation, so will use Degree of Automation as a surrogate measure of susceptibility to automation.

For this item the O*Net survey subjects are asked to rate the degree of automation of their current job on a five-point scale from "not at all automated" to "completely automated."

For the skill requirement measures we will use the Work Styles O*Net data set, which covers "personal characteristics that can affect how well someone performs a job." A description of the 16 Work Styles items is shown in the appendix. The Work Styles data primarily came from surveys of "job incumbents," i.e., individuals with experience in specific jobs. For a detailed description of how the Work Styles scales were developed see [15].

Creative skill requirement. The one Work Style items pertaining to creativity is "Innovation.". As shown in the appendix, the Innovation item measures if a job requires "creativity and alternative thinking to develop new ideas for and answers to work-related problems." The Innovation item is measured on a five-point scale, as are other Work Styles survey items.

Interpersonal skill requirement could be represented by various Work Styles data items. To narrow the list, we conducted Exploratory Factor Analysis on the Work Styles items using principle component analysis with a standard varimax rotation. The EFA resulted in three factors that met the Kaiser criterion (eigenvalues>1). One of the factors included the following items: Adaptability/ Flexibility, Concern for Others, Cooperation, Dependability, Integrity, Leadership, Self Control, Social Orientation, and Stress Tolerance. As can be seen in the appendix, these items all pertain to interpersonal skills.

To narrow the list we reviewed correlations (also shown in the appendix). We hypothesize that the interpersonal skill requirements will have a negative correlation with Degree of Automation. Three items that stand out include:

- Concern for Others ("Job requires being sensitive to others' needs and feelings and being understanding and helpful on the job.")
- Cooperation ("Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude.")
- Social Orientation ("Job requires preferring to work with others rather than alone, and being personally connected with others on the job.")

Professionalism may be defined various ways. For this study we focus on a basic definition of "requiring extensive preparation and training" which has been widely discussed in the literature [e.g., 16, 17-20]. The O*Net data contains information about job preparation and training. For this study we will focus on a measure called "Job Zones" which are listed in Table 1. Job Zone 5 ("advanced training and preparation") is considered the most professional. The table shows the number of jobs in each of five Job Zones, including the number in healthcare.

Table 1. O*Net Job Zones (HC=healthcare jobs)

Job Zone	Jobs	HC
1: "little or no preparation needed"	36	0
2: "some preparation needed"	294	8
3: "medium preparation needed"	245	40
4: "considerable preparation needed"	230	6
5: "extensive preparation needed"	161	50
Total	966	104

Note that the fifty zone-5 jobs are largely physicians and other medical practitioners, and the zone-3 jobs are often technicians or technologists. As hypothesized, we find that the technician/technologist jobs are more automated than the professional counterparts, as shown in Table 2.

Table 2. Job comparison (Degree of Automation)

Zone 5 Professional	Zone 3 Semi-professional
Neurologists (1.70)	Neurodiagnostic Technologists (2.15)
Nuclear Medicine Physicians (2.45)	Nuclear Medicine Technologists (2.49)
Pharmacists (2.63)	Pharmacy Technicians (2.68)
Radiologists (2.42)	Radiologic Technicians (2.80)
Surgeons (1.43)	Surgical Technologists (1.89)
Veterinarians (1.49)	Veterinary Technologists and Technicians (1.90)

A basic test of hypotheses H1a through H1c is simply to correlate the above-listed O*Net items with Degree of Automation. The alternate hypotheses assume that the items are barriers to automation meaning that the correlations will be negative. Table 3 shows correlation coefficients for these items using all 966 jobs in the O*Net data (additional correlations are included in the appendix). Note that all hypotheses are supported, and the items appear to be barriers to automation.

Table 3. Tests of hypotheses H1a-H1c

Job requirement O*Net data item	Corr. with Deg Auto	Hypothesis supported?
Creative skills		
Innovation	-.291***	H1a: yes
Interpersonal skills		
Concern for Others	-.201***	H1b: yes
Cooperation	-.093**	H1b: yes
Social Orientation	-.187***	H1b: yes
Professional training		
Job Zone	-.170***	H1c: yes

**p < .01, ***p < .001

The Table 3 statistics treat the O*Net items independently. There are likely to be correlations and relationships among the items. For example, we suppose that the primary purpose of professional training is to acquire skills, which may include creative skills and interpersonal skills. Therefore, we might hypothesize that requirements for creative and interpersonal skills are a mediating variable between professional training and automation, as depicted in Figure 1. The solid arrows represent the correlations depicted in Table 3. The dashed arrows represent the supposed moderating relationship.

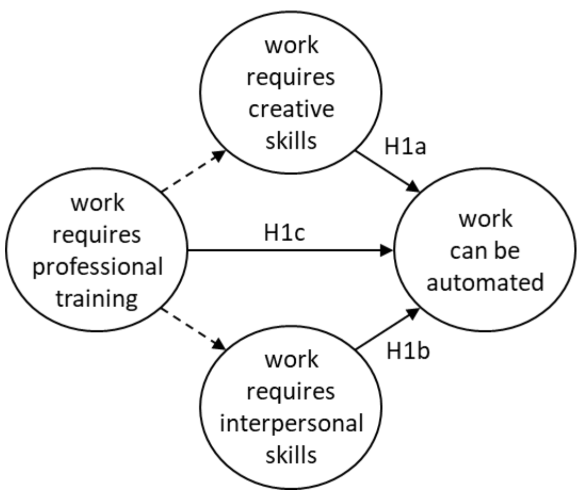

Figure 1. Moderated model

The idea behind the moderating relationships in Figure 1 is that professional training does not directly influence automation. This assumes that the decision to automate a given process is more a function of if the process can be automated and less a function of who is doing the process. Granted, there may be situations where professionally trained workers overtly attempt to limit automation, such as to preserve their livelihoods. Such situations would seem unlikely. Instead, the theory behind moderating relationships is that professional training is inversely correlated with Degree of Automation because professional training is positively correlated with skill requirements (as shown in Table 4), which skill requirements are inversely correlated with Degree of Automation.

Table 4. Summary of correlations

	1.	2.	3.	4.	5.
1. Degree of Automation					
2. Innovation	-.29				
3. Concern for Others	-.20	.12			
4. Cooperation	-.09	.24	.69		
5. Social Orientation	-.19	.14	.83	.72	
6. Job Zone	-.17	.52	.15	.24	.15

For an initial test of the moderating relationship we can simply regress the O*Net data items on Degree of Automation. Results are shown in Table 5.

Table 5. Joint test of hypotheses

DV:	Model 1	
Degree of Automation	β	t
Intercept	3.08	13.727***
Innovation	-.33	-8.236***
Concern for Others	-.21	-3.788***
Cooperation	.35	4.846***
Social Orientation	-.13	-2.290**
Job Zone	-.01	-.504
R^2	0.14	
F statistic	29.91	
p value	0.000	

**p < .01, ***p < .001

Note that Job Zone is no longer a significant predictor of Degree of Automation, suggesting that the effect of Job Zone is indeed represented by the other factors.

In that regression, the variance inflation factors (VIF) for Concern for Others and Social Orientation are 3.39 and 3.62 respectively. While those VIF values do not indicate egregious multicollinearity, the do exceed the conservative 3.0 threshold. An easy solution is to average the three interpersonal skills items into a single Interpersonal skills scale. That scale has a Cronbach's alpha of .880, indicating good reliability.

Regression results using this interpersonal skill requirement scale are shown in Table 6.

Table 6. Test with Interpersonal scale

DV:	Model 2	
Degree of Automation	β	t
Intercept	3.85	22.06***
Innovation	-.30	-7.40***
Interpersonal scale	-.11	-4.51***
Job Zone	-.00	-.12
R^2	0.10	
F statistic	37.32	
p value	0.000	

***p < .001.

Once again, the impact of Job Zone is completely absorbed by the combination of Innovation and the Interpersonal scale. Table 6 does not tell us where the indirect effect is taking place: with Innovation, Interpersonal, or both. We therefore regress including interaction terms. Results are shown in Table 7.

Table 7. Test with interaction terms

DV:	Model 3	
Degree of Automation	β	t
Intercept	3.82	21.56***
Innovation	-.33	-8.07***
Interpersonal scale	-.13	-3.38**
Job Zone	.00	.21
Job Zone x Innovation	-.02	-1.17
Job Zone x Interpersonal	-.06	-3.72***
R^2	0.12	
F statistic	25.972	
p value	0.000	

**p < .01, ***p < .001

We thus observe that Job Zone is moderated by Interpersonal skills. In other words, Job Zone is a predictor of automation as it correlates with interpersonal skills.

4. Tests using Healthcare subset

In this research we are specifically interested in observing if these hypotheses pertaining to job automation are also supported using the subset of O*Net data about healthcare jobs. As mentioned, 104 of the 966 jobs are in healthcare categories. Note from Table 1 that even though healthcare accounts for less than 11 percent of the overall jobs (not weighted for employment), healthcare has 31 percent of the Job Zone 5 jobs. Thus, almost one-third of all professional jobs are in healthcare. Twenty-five percent of U.S. professional (zone-5) jobs (weighted for employment) are in the healthcare. In the U.S., almost 6 percent of all jobs require professional training. Yet, almost 25 percent of healthcare jobs require professional training. In other words, healthcare is a major factor in the professional economy.

We graphically confirm that highly trained professional jobs are less automated. Figure 2 shows mean Degree of Automation scores for healthcare jobs by Job Zone (omitting the one zone 2 job). The dashed line shows the mean for all jobs, 2.02. The Zone 5 mean (1.84) is statistically different from the overall mean (p<.001), which suggests that hypothesis H1c is supported for healthcare jobs.

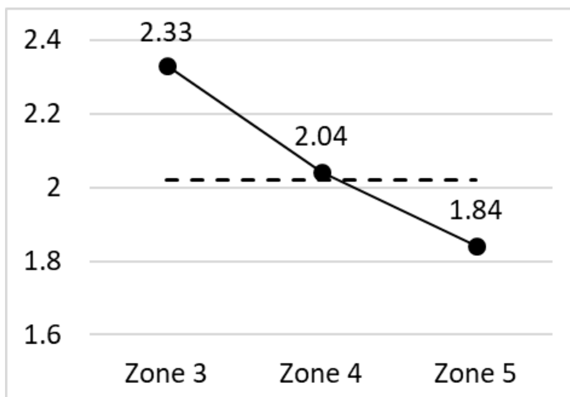

Figure 2. Degree of Automation by Job Zone

Table 8 shows a repeat of the test from Table 6 using the healthcare data subset.

Table 8. Test over Healthcare jobs (N=104)

DV:	Model 4	
Degree of Automation	β	t
Intercept	6.14	9.46***
Innovation	-.415	-3.33**
Interpersonal scale	-.481	-2.86**
Job Zone	-.139	-3.74***
R^2	0.37	
F statistic	19.49	
p value	0.000	

**p < .01, ***p < .001.

The Innovation item and Interpersonal scale are once again significant. However, with the healthcare subset the beta coefficient for Job Zone remains significant, which makes us suspect there may be no significant mediating effect. That suspicion is confirmed by regressing with the Job Zone interaction terms, neither of which wound up being significant.

We therefore conclude from Table 8 that for healthcare jobs, factors besides creative and emotional skill requirements contribute to the decreased automation of professional jobs.

5. Discussion

Technology forecasting can be very difficult, and job automation is advancing in surprising ways. In 2004, esteemed economists Frank Levy (from MIT) and Richard Murnane (from Harvard) published a book about how computers transform the job market [21]. They described both the capabilities of computer automation and limitations. They assert that while task simplification makes it possible to automate many business interactions, something as complex as a truck driver making a left turn is not likely to be automated. It is clear that self-driving vehicles are on the near horizon.

On the healthcare front they quote a medical clinician who asserts that computer algorithms are good at simple radiological diagnosis of breast cancer, but not as good at detecting subtle masses. Again, current technologies have been reported to rival human radiologists in performance. (Two experts stated, “In many radiology applications, eg, mammography and colon CAD, computerized CADx systems have shown comparable, or even higher, performance compared with well-trained and experienced radiologists and technologists.” [22, p. 946])

An important research question is where automation is likely to impact jobs and which of the jobs’ tasks are likely to be impacted first. The literature and our research suggests that creative and interpersonal jobs are less likely to be automated, both for healthcare jobs and jobs in general. However, that is somewhat of a naïve view, since even a creative/interpersonal job is likely to include elements that require neither creative skills nor interpersonal skills.

There are various possible explanations for why, with the O*Net healthcare job data, Job Zone continued to regress on Degree of Automation independent from Innovation measure and the Interpersonal scale. This may just be a random effect, the results of the smaller data set. Or, it may be due to some artifact of the healthcare industry.

Remember that healthcare has a disproportionate number of Job Zone 5 professionals. Further, these professionals wield a significant amount of influence over how healthcare professions operate. One theory for their unusually low levels of job automation may pertain to technology adoption including resistance to change. Evidence may come from research applying technology adoption models to healthcare [23].

Healthcare is presumed to be an industry that is more regulated than most. A second theory for the unusually low automation of healthcare professionals is that regulation may limit the infusion of new technologies, including information technologies that may put patient privacy at risk. Compliance may come at high cost, which would be a disincentive to change and technological innovation. Case studies on privacy regulations (e.g. HIPAA) might shed insights.

Healthcare in the U.S. (where the O*Net data comes from) involves payments coming from a complex network of individuals, private insurers and government agencies. Much of healthcare is governed by the payment rules and regulations. A third theory for the unusually low automation of professional jobs in healthcare is the payment structure. Automation usually changes the economics of service delivery, often lowering the cost of delivery, perhaps at a high fixed cost. Healthcare professionals may have a disincentive for adopting automation in terms of lost revenues through increased efficiency. An example is telemedicine where physicians may see more patient without the overhead of a clinic visit, at lower billing rates. Comparative studies of different healthcare payment models could provide insights.

6. Limitations and Future Research

Our predictive model of automaton only considered factors described in recent literature, but did not attempt to expand the list of factors. As more data becomes available we might consider a wider variety of factors that inhibit or promote automation.

For this exploratory study we were limited by the available O*Net data. We only had a single survey item for the creative skills construct and three items for the interpersonal skills construct. Future research can look at developing more complex multi-item scales for these and other relevant job characteristics.

We studied automation at the job level, when in fact it is specific tasks within jobs that are automated or not automated. Future research might look at the tasks performed by healthcare professionals and identify task characteristics that relate to automation.

We only considered aggregate O*Net data from one country with a healthcare system that is atypical among worldwide health systems. Again, comparative studies involving multiple countries might shed expanded insights.

Also, this research focused on only the healthcare subset of the O*Net data. Extensions of the research might look at if these relationship occur in other professional services, or in jobs that are not professional services.

Finally, there are many other characteristics of healthcare jobs that might influence susceptibility to automation, such as accountability, transparency, and privacy. Those items are not included in the O*Net Work Styles data, but other O*Net data sets might be consulted for expanded analysis.

7. Summary and Conclusion

In summary, we observe that healthcare jobs that require professional training are indeed less automated than other healthcare jobs, and that this could at least partially be explained by requirements for creative and interpersonal skills. The relationship between professional training and automation appears to be partially moderated by interpersonal skill requirements, suggesting that resistance to automation of professional jobs is heightened when the jobs also require interpersonal skills.

This study considers automation at what is considered the top of the skill latter: highly trained professionals. In the past, professional jobs have not experienced the degree of automation experienced in manual labor jobs or semi-professional jobs. Advances in AI and other technologies are likely to change that in coming years. Jobs and tasks that were resistant to automation in the past may be automated in the future. Not only are automation technologies becoming more capable but users of technology are becoming more open. In time, the current core of healthcare professionals and patients may be replaced by younger people who are more technologically inclined.

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Appendix

O*Net Work Styles survey items

Work Style item	Item description (with O*NET survey element ID)
Achievement/Effort	Job requires establishing and maintaining personally challenging achievement goals and exerting effort toward mastering tasks. (1.C.1.a)
Adaptability/Flexibility	Job requires being open to change (positive or negative) and to considerable variety in the workplace. (1.C.4.c)
Analytical Thinking	Job requires analyzing information and using logic to address work-related issues and problems. (1.C.7.b)
Attention to Detail	Job requires being careful about detail and thorough in completing work tasks. (1.C.5.b)
Concern for Others	Job requires being sensitive to others' needs and feelings and being understanding and helpful on the job. (1.C.3.b)
Cooperation	Job requires being pleasant with others on the job and displaying a good-natured, cooperative attitude. (1.C.3.a)
Dependability	Job requires being reliable, responsible, and dependable, and fulfilling obligations. (1.C.5.a)
Independence	Job requires developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done. (1.C.6)
Initiative	Job requires a willingness to take on responsibilities and challenges. (1.C.1.c)
Innovation	Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems. (1.C.7.a)
Integrity	Job requires being honest and ethical. (1.C.5.c)
Leadership	Job requires a willingness to lead, take charge, and offer opinions and direction. (1.C.2.b)
Persistence	Job requires persistence in the face of obstacles. (1.C.1.b)

Work Style item	Item description (with O*NET survey element ID)
Self Control	Job requires maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations. (1.C.4.a)
Social Orientation	Job requires preferring to work with others rather than alone, and being personally connected with others on the job. (1.C.3.c)
Stress Tolerance	Job requires accepting criticism and dealing calmly and effectively with high stress situations. (1.C.4.b)

Descriptive statistics and correlations for Degree of Automation and Work Styles items.

		Mean	*SD*	**1.**	2.	3.	4.	5.	6.	7.
1.	**Degree of Automation**	2.16	.54							
2.	Achievement/Effort	3.84	.39	**-.14****						
3.	Adaptability/Flexibility	3.98	.37	**-.16****	.55**					
4.	Analytical Thinking	3.85	.58	**-.07***	.66**	.42**				
5.	Attention to Detail	4.42	.31	**.05**	.48**	.37**	.52**			
6.	Concern for Others	3.78	.55	**-.20****	.21**	.53**	.03	.08**		
7.	Cooperation	4.13	.34	**-.09****	.35**	.67**	.19**	.28**	.69**	
8.	Dependability	4.41	.28	**-.09****	.45**	.64**	.29**	.47**	.57**	.64**
9.	Independence	3.92	.38	**-.21****	.51**	.46**	.45**	.31**	.38**	.32**
10.	Initiative	4.03	.37	**-.20****	.80**	.65**	.66**	.41**	.31**	.46**
11.	Innovation	3.54	.48	**-.29****	.61**	.49**	.63**	.30**	.12**	.24**
12.	Integrity	4.33	.43	**-.10****	.51**	.56**	.54**	.45**	.46**	.54**
13.	Leadership	3.65	.53	**-.18****	.56**	.60**	.46**	.22**	.49**	.55**
14.	Persistence	3.91	.39	**-.19****	.85**	.61**	.67**	.44**	.22**	.36**
15.	Self Control	4.04	.41	**-.11****	.26**	.60**	.08*	.18**	.78**	.67**
16.	Social Orientation	3.40	.56	**-.19****	.26**	.57**	.02	.05	.83**	.72**
17.	Stress Tolerance	3.99	.43	**-.03**	.47**	.71**	.30**	.37**	.59**	.63**

Table continued…

		8.	9.	10.	11.	12.	13.	14.	15.	16.
9.	Independence	.48**								
10.	Initiative	.51**	.54**							
11.	Innovation	.26**	.52**	.67**						
12.	Integrity	.60**	.49**	.56**	.30**					
13.	Leadership	.51**	.37**	.69**	.49**	.47**				
14.	Persistence	.45**	.51**	.84**	.62**	.51**	.58**			
15.	Self Control	.64**	.36**	.34**	.09**	.54**	.49**	.29**		
16.	Social Orientation	.54**	.29**	.33**	.14**	.42**	.52**	.24**	.77**	
17.	Stress Tolerance	.65**	.37**	.51**	.23**	.55**	.56**	.52**	.76**	.62**

$^*p < 0.05$, $^{**}p < 0.01$, all O*Net jobs ($n = 966$).