INDUSTRY 4.0 AND SHORT-TERM OUTLOOK FOR AEC INDUSTRY WORKFORCE

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Emilio J. Quintana

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INDUSTRY 4.0 AND SHORT-TERM OUTLOOK FOR AEC INDUSTRY WORKFORCE

Approved by:

Dr. Baabak Ashuri
Schools of Building Construction, and Civil & Environmental Engineering
Georgia Institute of Technology

Dr. Javier Irizarry
School of Building Construction
Georgia Institute of Technology

Dr. Bryan Franz
M.E. Rinker, Sr. School of Construction Management
University of Florida

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SUMMARY

Technology is uniquely transforming our society to a significant degree. This transformation has been described as Industry 4.0 and encompasses machine learning, computerization, automation, artificial intelligence, and robotics. Industry 4.0 is currently impacting the United States' workplace and is projected in continue uniquely changing our society over the next twenty years or so. Looking specifically at the AEC industry, this paper researches how the AEC industry workplace could be impacted by Industry 4.0 over the next several years. The hypothesis that jobs more at risk for automation should see low or negative growth and lower wages over the next several years was tested by using U.S. Bureau of Labor Statistics (BLS) occupational wage data and growth projections to create an opportunity value for each occupation, and then evaluating the relationship between the opportunity value and probability of automation. A statistical significance was found between the two variables. The hypothesis that certain skills are particularly associated with high growth/high wage jobs versus low growth/low wage jobs was tested by scraping important skills/qualities from the individual occupational webpages hosted by the U.S. Bureau of Labor Statistics, and then comparing the approximately top 80% of skills scraped between the two groups. Certain skills/qualities were found to be particularly associated with each group. Finally, the occupations associated with the AEC industry were compared with the findings from the first two hypotheses. The discoveries were that the AEC industry is potentially more susceptible to Industry 4.0 than other industries. This research is of significance because research into how the AEC industry workplace will be impacted by Industry 4.0 over the next several years was not found in the research background, and it has implications on potential

career choices, skill requirements, and areas of research and development. Recommendations for future work include utilizing new data sources, Monte Carlo simulations, cohort analysis, and cluster analysis to make more specific forecasts on Industry 4.0's impact on the AEC industry.

CHAPTER 1: RESEARCH MOTIVATION AND QUESTION STATEMENT

1.1: RESEARCH MOTIVATION

TIME recently published an article reporting that robots and artificial intelligence are currently replacing jobs in the United States economy.[1] TIME and Forbes have both reported that the replacement of occupations by robots and artificial intelligence is expected to increase in the coming years. [1, 2] The COVID-19 pandemic is stated as potentially accelerating the speed at which companies are implementing new technologies.[1] Robots are appealing to businesses as they do not get sick, require time off, need to isolate, and are more consistent when compared with a human workforce. This has major implications on the United States' economy as we know it. Indeed, TIME gave an account that a group of economists believe that 42% of the 40 million jobs lost due to COVID-19 are lost forever.[1]

In the AEC industry, the Robotics Business Review put out an article suggesting that more than seven thousand robots will work in the construction industry by 2025.[3] Wired.com and the San Francisco Business Times both reported on the very recent reveal of a drywall finishing robot by the robotics startup Canvas. Their robot has the potential to reduce the costs and time associated with drywall finishing.[4, 5] Additionally, Engineering.com newly announced that Trimble and Boston Dynamics are partnering to increase the use of robots and artificial intelligence in the construction industry.[6] These articles are evidence that the AEC industry will certainly be affected by this wave of technological advances. Where does the AEC industry stand in relation to other industries in terms of artificial intelligence, and how will these changes impact its workforce?

This is area of significance as it has implications into whether young people should choose careers in the AEC industry, what kind of research, development, and workforce training both private and public organizations should invest in, and what skills are required to be successful in near future.

1.2: RESEARCH QUESTION STATEMENT

Although the AEC industry is behind the curve in implementing both new and existing technologies, predictions suggest that Industry 4.0 will have made massive impacts to the United States' workplace in less than 15 years, impacts that the AEC workplace will not be immune to. Looking specifically at the AEC industry, what do these predictions suggest for the AEC industry's workplace in the coming years?

CHAPTER 2: RESEARCH BACKGROUND

2.1: INDUSTRY 4.0 & IMPACTS ON THE UNITED STATES' WORKPLACE

In his 2016 book, *The Fourth Industrial Revolution*, World Economic Forum Founder and Executive Chairman, Klaus Schwab discussed how technology will uniquely transform our societies in a, "scale, scope, and complexity," to be considered the fourth industrial revolution,[7] also known as Industry 4.0.[7, 8] Industry 4.0 describes the overall societal transformation caused by a variety of technologies, and it encompasses fields of study such as machine learning, computerization, automation, artificial intelligence, and robotics.[9, 10] Today, non-routine tasks, like driving a car in city traffic, that were once not adequately understood enough to be automated are now in the realm of automation.[11]

Technological changes have already had an impact on the economy of the United States. Using a task-based model, Autor, Levy, and Murnane showed that computerization has altered job skill demands.[11] Due to this shift in job skill demands, we have seen a significant decrease in the wages of low skill worker, while also seeing an increase in the wages of high skill workers.[12, 13] This has contributed to the increase in the wage gap.[12, 13] Additionally, when compared to middle skilled occupations, there has been greater growth in the employment of low skill and high skill workers, leading to job polarization.[12] The percentage of middle income jobs are projected to shrink as automation continues to increase.[14]

One conjecture is that only certain industries or sectors will be impacted by technological changes (i.e. manufacturing); however, the research indicates that the computerization and automation of occupations is driven by which skills make up jobs rather than the industry or sector that those jobs are in.[15] Therefore, many occupations and careers will be impacted in the next wave of automation, in which the field of artificial intelligence is a driving force.[14, 16]

In 2013, Carl Benedikt Frey and Michael Osborne of Oxford University utilized a Gaussian process classifier to estimate the probability of 702 occupations being replaced by computerized automation.[17] They predicted that, "around 47% of total US employment is in the high risk category. We refer to these as jobs at risk – i.e. jobs we expect could be automated relatively soon, perhaps over the next decade or two."[17] In 2017 McKinsey & Company predicted that 51% of activities in the United States economy could be automated as early as 2035, and as late as 2075 depending on varied market and economic conditions.[18] They also estimated that 46% of activities in the United States economy could be automated by adapting currently available technologies.[18] Automatable jobs are notably more likely to be held by young people and people with a high school degree or less.[14, 15] This suggests that young people will need to find different solutions than previous generations in order to have viable options in the labor market.

One gap in the knowledge is how the different factors found to be associated with occupations' susceptibility to automation are related to each other (i.e. how are the task-based model and projected growth of low wage jobs related). Another gap in the knowledge is which specific skills are associated with projected high growth vs low growth occupations. Finally, the literature was focused on the economy as a whole, and an additional gap in knowledge is how specific industries will be impacted by automation.

2.2: INDUSTRY 4.0 & IMPACTS TO THE AEC INDUSTRY

The architecture, engineering, and construction (AEC) industry is classified as a middle skill industry, indicating that it will be disproportionately impacted by artificial intelligence and automation.[12, 14, 15] Indeed, the percentage of high skilled jobs in the AEC industry has noticeably increased from 1983 to 2012.[15] Correlated with this growth in the number of high skilled jobs has been a shortage of skilled workers within the AEC industry since the early 1980s.[19]

While there has been an increase in high skilled jobs in the AEC industry, it still has a large proportion of jobs that only require a high school degree or equivalent for entry, thereby also indicating that it will be unequally affected by artificial intelligence and automation.[14, 15, 20] This high concentration of a low-educated workforce could assist in explaining how the AEC industry accounted for approximately 52% of the job losses during the Great Recession.[21] Job polarization accelerates during recessions, and Groshen and Potter promulgate that a portion of the jobs lost during the Great Recession were permanent.[15, 22]

The evolution of AI research has been one of systole and diastole—that is, research and funding has ebbed and flowed over time, often correlated with breakthroughs on the one hand, and unmet expectations on the other.[23-25] Nevertheless, the overall trend of AI research in the AEC industry has been one of substantial growth.[26] Using a scientometric science mapping analysis method, Darko et al., "systematically and quantitatively analyze 41,827 related bibliographic records," of research on artificial intelligence in the AEC industry.[26] Their examination indicates that research in the field of artificial intelligence has seen significant, if not exponential, growth between 1974 and 2019.[26] The main focus areas of artificial intelligence research in the AEC industry has been machine learning, optimization, fuzzy logic, genetic algorithm, fuzzy sets, and neural networks, with little attention being paid to robots.[26]

The AEC industry has been slow to implement artificial intelligence,[27] and the focus of AI research in the AEC industry up to this point in time has been optimizing traditional construction methods (i.e. scheduling, and cost management). Of twelve industries examined, ten of them were ahead of the AEC industry in artificial intelligence implementation.[27] As the AEC industry continues to adopt artificial intelligence, we may initially see an increase in jobs as demand is elastic, and then see high job losses as demand shifts towards inelastic. We have seen this trend in the past as the textile, auto, and steel industries adopted new technologies.[13]

In a field where traditionally, workers need to be onsite to complete physical tasks, robotics may be the greatest threat of job automation in the AEC industry, though perhaps the furthest from fruition. A subfield of artificial intelligence,[28] robotics is the modeling and fabrication of machines that can perform tasks.[29] While robots that can fully replace humans in the working environment is an area of aspiration,[29] there may be a rise in collaborative robots, robots that work directly with humans,[30] before we see a dramatic rise in robots that fully replace human workers.

In the research background, research into how the AEC industry workplace will be impacted by Industry 4.0 over the next several years was not found. Where does the AEC industry fall in terms of known factors associated with occupations' susceptibility to replacement by technology?

CHAPTER 3: RESEARCH GOAL & OBJECTIVES

My research goal is to explore how Industry 4.0 could impact the AEC industry workplace over the short term. The first research objective is to test the hypothesis that jobs more at risk for automation should see low or negative growth and lower wages over the next several years. The second research goal is to test the hypothesis that the likelihood of automation of occupations is driven by which skills make up those jobs rather than the industry or sector that those jobs are in. The third and final research objective is to assess and evaluate the findings of the first two objectives with the occupations that make up the AEC industry specifically.

CHAPTER 4: GROWTH & WAGE PROJECTIONS VS LIKELIHOOD OF AUTOMATION

The initial step of the data analysis was to access the most recent *Occupational Outlook Handbook* from the U.S. Bureau of Labor Statistics. The data was readily available online, and the *Occupation Finder* tool was used to look at the 790 occupations on which data was available in aggregate. The data from this source had the following information, each corresponding to a column: occupation, entry-level education, on-the-job training, projected number of new jobs, projected growth rate, and 2019 median pay.[31]

Next, the data was copy and pasted into Microsoft Excel 2016 for examination. Beginning with the *2019 Median Pay* column, frequency tables were then created to survey the categories in which the data was classified by the U.S. Bureau of Labor Statistics (Table 4.1). Data was not available for five (5) occupations' 2019 median pay, and these occupations were removed from further analysis, thereby bringing the total number of occupations analyzed to 785. The occupations removed were: actors, dancers, fishing and hunting workers, miscellaneous entertainers and performers, sports and related workers, and musicians and singers.

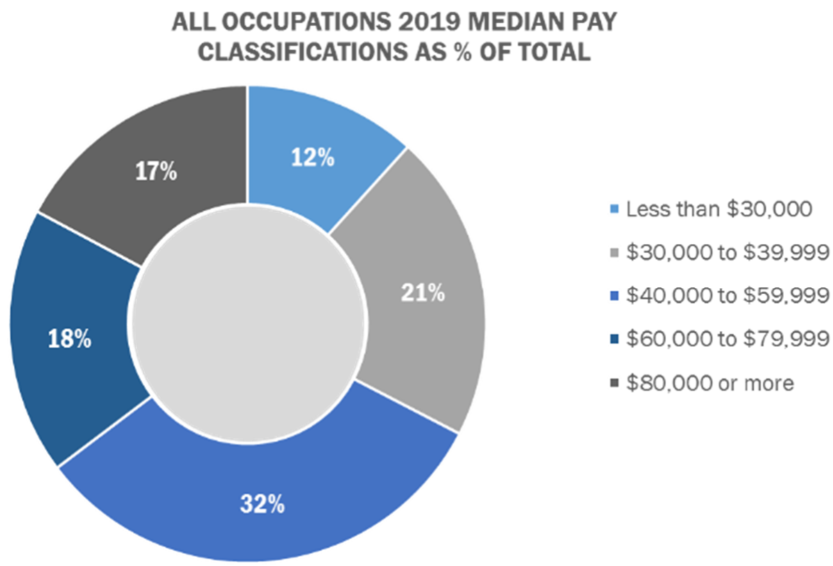

Figure 4.1: The distribution of 2019 Median Pay classifications for all Occupations. The table was created using Microsoft Excel 2016's Doughnut Chart function and Microsoft PowerPoint 2016. *

*For the figures and tables in this chapter, data was obtained from the U.S. Bureau of Labor Statistics website on October 10, 2020 and Frey & Osborne's data published in 2016. Georgia Institute of Technology, Atlanta, Georgia.

Table 4.1: Frequency of 2019 Median Pay classifications for all Occupations. The table was created using Microsoft Excel 2016's PivotTable function.

ALL OCCUPATIONS 2019 MEDIAN PAY CLASSIFICATION FREQUENCY TABLE	
Row Labels	**Count of 2019 MEDIAN PAY**
Less than $30,000	92
$30,000 to $39,999	164
$40,000 to $59,999	252
$60,000 to $79,999	142
$80,000 or more	135
Grand Total	**785**

The objective of the next phase was to assign each occupation a value based on the available data. According to the background research, jobs more at risk for automation should see low or negative growth and lower wages over the next several years. Therefore, the available data utilized to create this value were projected number of new jobs, projected growth rate, and 2019 median pay. Entry-level education and on-the-job training were excluded from calculating the value as they are not factors in the first hypothesis.

Table 4.2: The data classifications and assigned values (AV). The table was created using Microsoft Excel 2016.

NUMERICAL VALUE ASSIGNED TO EACH CLASSIFICATION	CLASSIFICATIONS
2019 MEDIAN PAY	
1	Less than $30,000
2	$30,000 to $39,999
3	$40,000 to $59,999
4	$60,000 to $79,999
5	$80,000 or more
PROJECTED GROWTH RATE	
0	Decline
1	Little or no change
2	Slower than average
3	As fast as average
4	Faster than average
5	Much faster than average
PROJECTED NUMBER OF NEW JOBS	
0	Declining
1	0 to 999
2	1,000 to 4,999
3	5,000 to 9,999
4	10,000 to 49,999
5	50,000 or more

To assign each occupation a value based on the available data, values were assigned to each classification in the following columns: projected number of new jobs, projected growth rate, and 2019 median pay (Table 4.2). Negative classifications (i.e. declining) were given the value of zero. Positive classifications were given integer values from one to five. The more apparent demand, the higher the respective number. Following, Microsoft Excel's IF function was used to create columns of values based on the classification and its assigned value (AV) (Figure 4.2). Finally, another column with the sum of the assigned values for each occupation was added using Microsoft Excel (Figure 4.3). The sum of the assigned values is the occupation's opportunity value.

=IF(E2="Declining",0,IF(E2="0 to 999",1,IF(E2="1,000 to 4,999",2,IF(E2="5,000 to 9,999",3,IF(E2="10,000 to 49,999",4,IF(E2="50,000 or more",5))))))

Figure 4.2: The Microsoft Excel 2016's IF function equation used to assign the designated values to each occupation based on the data classification of Projected Number of New Jobs.

		BLS DATA			ASSIGNED VALUES			
	OCCUATION	PROJECTED # OF NEW JOBS	PROJECTED GROWTH RATE	2019 MEDIAN PAY	PROJECTED # OF NEW JOBS	PROJECTED GROWTH RATE	2019 MEDIAN PAY	TOTAL
1	Accountants and auditors	50,000 or more	As fast as average	$60,000 to $79,999	5	3	4	12
2	Actuaries	1,000 to 4,999	Much faster than average	$80,000 or more	2	5	5	12
3	Acupuncturists and healthcare diagnosing or treating practitioners, all other	Declining	Little or no change	$60,000 to $79,999	0	1	4	5
4	Adhesive bonding machine operators and tenders	Declining	Decline	$30,000 to $39,999	0	0	2	2
5	Administrative law judges, adjudicators, and hearing officers	0 to 999	Little or no change	$80,000 or more	1	1	5	7

Figure 4.3: Image displaying the Microsoft Excel file of the data (the Occupational Outlook Handbook data from the U.S. Bureau of Labor Statistics with the added columns containing the assigned values and sum total of the assigned values).

Subsequently, the values of the occupations, based on the U.S. Bureau of Labor Statistics data, were evaluated in comparison to the probabilities of automation of those same occupations based on the article *The future of employment: How susceptible are jobs to computerisation?* Originally published in 2013, Carl Benedikt Frey and Michael Osborne of Oxford University utilized a Gaussian process classifier to estimate the probability of 702 occupations being replaced by computerization, which they define as, "as job automation by means of computer-controlled equipment."[17] Each occupation's value as evaluated in comparison to the probability of each occupation's computerization to see if growth projections and wages are related to the probability of automation.

To begin, the data from Appendix A of *The future of employment: How susceptible are jobs to computerization?,* was copied and pasted into Microsoft Excel 2016. The data from this source had the following information, each corresponding to a column: rank, probability (*of computerization), label, SOC code, and occupation. Using Microsoft Excel's sort function, the data was organized alphabetically based on the occupation.

Next, the data from the U.S. Bureau of Labor Statistics was copied and pasted into the same workbook for comparison. Using Microsoft Excel's match function, the occupations from both sets of data were evaluated for exact counterparts. Occupations that were not highlighted as exact counterparts were then reviewed by the author. Slight variations in spelling and semantics (i.e. Education administrators, elementary and secondary school, vs. Education administrators, kindergarten through secondary school) were considered equals with the author erring on the side of caution so as to maintain the integrity of the evaluation. After this process, 642 occupations were considered equivalent in both data sets.

Following, now that the occupations and corresponding data from both sets were aligned, the data was sorted based on the probability of occupation computerization from smallest to largest. Next, the occupations opportunity values and probability of occupation computerization were graphed using Microsoft Excel 2016 to visually compare the data for an overall trend (Figure 4.4). A relationship between the two values was visually evident in the analysis.

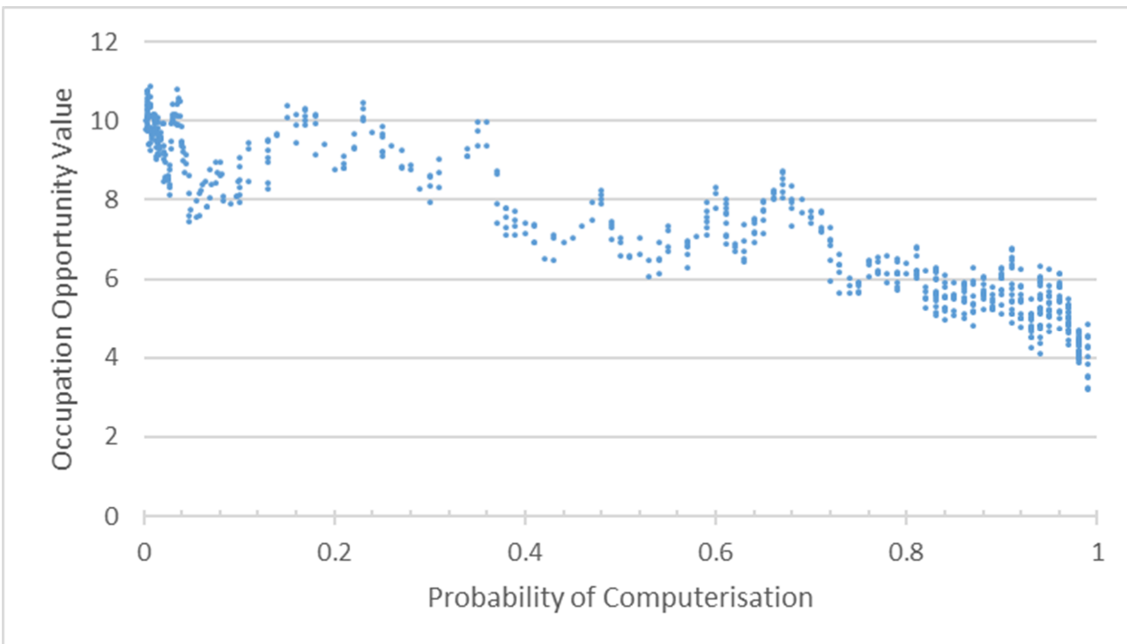

Figure 4.4: The relationship between occupations' opportunity value and probability of automation from Frey & Osborne's data. The plot was produced by exponentially smoothing the opportunity value with a dampening factor of 0.9. The chart was created using Microsoft Excel 2016.

The Kolmogorov-Smirnov test (K-S test) is used to test whether data has a specific distribution. "The Kolmogorov-Smirnov test statistic is defined as

$D = \frac{max}{1 \leq i \leq N}(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i))$, where F is the theoretical cumulative distribution of the distribution being tested."[32] A K-S test for normality, that is testing whether the data is normally distributed, was conducted using IBM SPSS Statistics software. The results for each variable rejected the null hypothesis ($p < \alpha$ where $\alpha = 0.05$) in favor of the alternative hypothesis—the data are not normally distributed.

Another test for normality was run using IBM SPSS Statistics software. The Shapiro-Wilk test, "calculates a W statistic that tests whether a random sample, $x_1, x_2, \ldots, x_n$ comes from (specifically) a normal distribution… The W statistic is calculated as follows: $W = \frac{(\sum_{i=1}^{n} a_i x_{(i)})^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$, where the x_i are the ordered sample values (x_1 is the smallest) and the a_i are constants generated from the means, variances and covariances of the order statistics of a sample of size n from a normal distribution."[33] As with the Kolmogorov-Smirnov test, the results for each variable rejected the null hypothesis ($p < \alpha$ where $\alpha = 0.05$) in favor of the alternative hypothesis—the data are not normally distributed.

Table 4.3: The results of the Kolmogorov-Smirnov and Shapiro-Wilk tests of the predictor variables computed using IBM SPSS Statistics version 28.0.0.0(190). The dependent variable is the probability of computerization based on Frey & Osborne's data.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
NewJobs	.178	640	<.001	.867	640	<.001
Growth	.207	640	<.001	.853	640	<.001
MedianSalary	.185	640	<.001	.909	640	<.001

a. Lilliefors Significance Correction

Next, quantile-quantile (q-q) plots and histograms were produced to graphically determine if the data sets shared a common distribution. The results also illustrated that the data sets do not share a common distribution. Examples of the histograms and detrended normal q-q plots and are shown below:

$$r_s = \frac{\frac{(n^3 - 3)}{6} - \sum_{i=1}^{n} d_i^2 - \sum T_x - \sum T_y}{\sqrt{\left[\frac{(n^3 - 3)}{6} - 2\sum T_x\right]\left[\frac{(n^3 - 3)}{6} - 2\sum T_y\right]}}$$

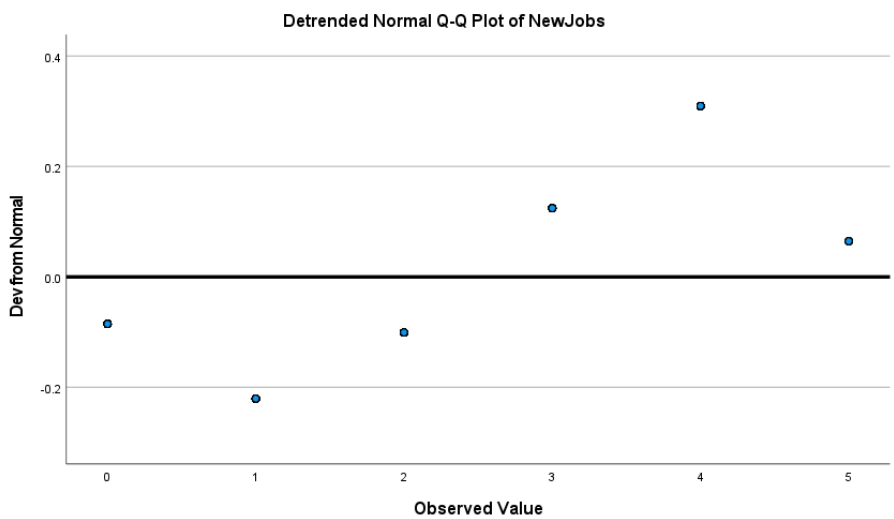

Figure 4.5: Example of the quantile-quantile (q-q) plots produced in IBM SPSS Statistics version 28.0.0.0(190).

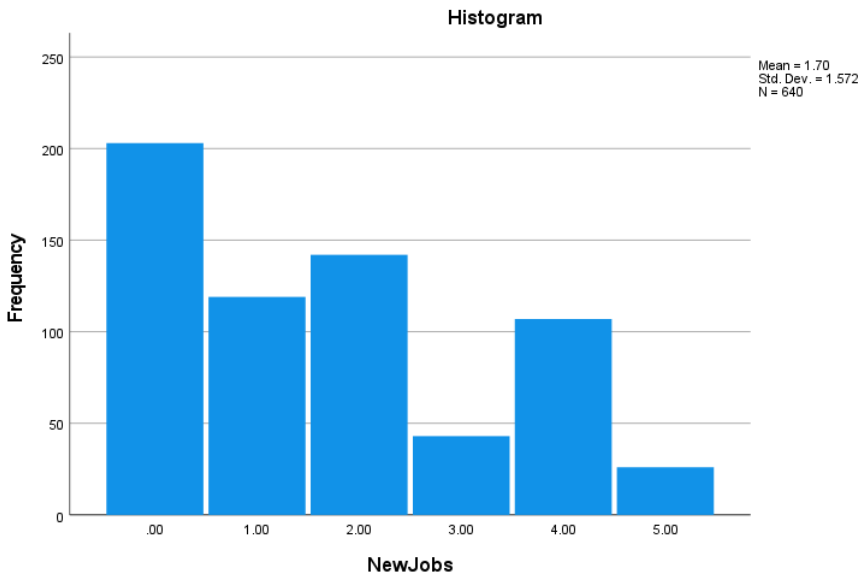

Figure 4.6: Example of the histograms produced in IBM SPSS Statistics version 28.0.0.0(190).

As the data was determined to be not normally distributed, nonparametric statistical tests were conducted. First, using the programming language R and IBM SPSS Statistics software, the Spearman rank correlation coefficient, ρ, was calculated to assess the degree of linear relationship between Frey & Osborne's data, and the opportunity value and each variable comprising the opportunity value. The equation for the Spearman rank correlation coefficient is: $r_s = \frac{\frac{(n^3-3)}{6} - \sum_{i=1}^{n} d_i^2 - \sum T_x - \sum T_y}{\sqrt{\left[\frac{(n^3-3)}{6} - 2\sum T_x\right]\left[\frac{(n^3-3)}{6} - 2\sum T_y\right]}}$, "where d_i is the difference between ranks for each $x_{i,}y_i$ data pair and n is the number of data pairs," and $\sum T_x = \frac{\sum_{j=1}^{g}\left(t_j^3 - t_j\right)}{12}$ (for x values) and $\sum T_y = \frac{\sum_{j=1}^{g}\left(t_j^3 - t_j\right)}{12}$ (for y values), "where g is the number of tied groups and t_j is the number of tied data in the jth group."[34] The Spearman rank correlation coefficient, ρ, was calculated to be -0.49388 for the 640 observations, thereby signifying a relationship between the data sets (Figure 4.7)

```
        Spearman's rank correlation rho

data:  my_data$oxford_study and my_data$desirability_value
S = 65268689, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
       rho
-0.4938854
```

Figure 4.7: The results of the Spearman's rank correlation calculation computed using R version 4.0.3 (2020-10-10). Variable 1 is the occupations' probability of computerization based on Frey & Osborne's data, and Variable 2 is the occupations' opportunity values.

Table 4.4: The results of the Spearman's rank correlation calculation of the predictor variables, computed using IBM SPSS Statistics version 28.0.0.0(190).

Correlations

			NewJobs	Growth	MedianSalary	FreyOsborne
Spearman's rho	NewJobs	Correlation Coefficient	1.000	.832**	.128**	-.333**
		Sig. (2-tailed)	.	<.001	.001	<.001
		N	640	640	640	640
	Growth	Correlation Coefficient	.832**	1.000	.163**	-.363**
		Sig. (2-tailed)	<.001	.	<.001	<.001
		N	640	640	640	640
	MedianSalary	Correlation Coefficient	.128**	.163**	1.000	-.503**
		Sig. (2-tailed)	.001	<.001	.	<.001
		N	640	640	640	640
	FreyOsborne	Correlation Coefficient	-.333**	-.363**	-.503**	1.000
		Sig. (2-tailed)	<.001	<.001	<.001	.
		N	640	640	640	640

**. Correlation is significant at the 0.01 level (2-tailed).

To evaluate how much of the variation in Frey and Osborne's data could be explained by projected number of new jobs, projected growth rate, and median pay, the R-Squared value was calculated in IBM SPSS Statistic software. The resulting R-Squared value was 0.342, indicating that approximately one-third of the variation in Frey and Osborne's data can be explained by the independent variables of jobs, projected growth rate, and median pay.

Table 4.5: The results of the R-Squared value calculation, computed using IBM SPSS Statistics version 28.0.0.0(190).

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.585[a]	.342	.339	.30118

a. Predictors: (Constant), MedianSalary, NewJobs, Growth

Next, the variance inflation factors (VIF) were calculated for each variable, using IBM SPSS Statistics software, to detect for multicollinearity.[35] Multicollinearity is when a predictor variable has a linear relationship with another predictor variable and can therefore misrepresent the data and its interpretation.[36] The VIF equation for variable X_i is: $VIF_i = (1 - {R_i}^2)^{-1}$ where ${R_i}^2$ is the coefficient of multiple determination when X_i is regressed against other predictor variables.[37] For predictor variables, VIF values greater than four (4) should be investigated further, and VIF values greater than ten (10) indicate acute multicollinearity that needs to be addressed. All VIF values were less than three (3), demonstrating that multicollinearity is not present in the data.

Table 4.6: The results of the VIF calculations of the predictor variables, computed using IBM SPSS Statistics version 28.0.0.0(190).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.102	.034		32.758	<.001		
	NewJobs	-.026	.012	-.109	-2.053	.040	.369	2.712
	Growth	-.037	.010	-.191	-3.578	<.001	.362	2.764
	MedianSalary	-.143	.010	-.470	-14.385	<.001	.968	1.033

a. Dependent Variable: FreyOsborne

Finally, using a matrix of the predictor variables, the eigenvalues (λ) were calculated and used to measure for multicollinearity in the data. An eigenvalue close to zero (0) implies that there is multicollinearity present. The condition index is, "the square root of the maximum and each eigenvalue ($\lambda_1, \lambda_{2,\ldots}\lambda_p$)," [38] and is defined as:

$$K_j = \sqrt{\frac{\lambda_{max}}{\lambda_j}}, j = 1,2, \ldots, p$$

A value of ten (10) or greater implies multicollinearity is present and a value greater than thirty (30) indicates acute multicollinearity that needs to be addressed. All condition index values calculated for the data were below ten (10), thus showing that multicollinearity is not present in the data.

Table 4.7: The results of the eigenvalues (λ) and condition indices of the predictor variables, computed using IBM SPSS Statistics version 28.0.0.0(190)

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	NewJobs	Growth	MedianSalary
1	1	3.414	1.000	.01	.01	.01	.01
	2	.429	2.820	.06	.13	.06	.09
	3	.086	6.296	.09	.76	.87	.02
	4	.070	6.962	.84	.09	.06	.88

a. Dependent Variable: FreyOsborne

In summary, there is a correlation and statistical significance between Frey and Osborne's 2013 analysis and predictions of the probability of occupations being automated by computerization, and the opportunity value of occupations assessed based on growth projections and wage date from the U.S. Bureau of Labor Statistics for the years 2019-2029. These findings reject the null hypothesis that there is not a relationship between the variables and affirms that a relationship does exist, thereby supporting the hypothesis that jobs more at risk for automation should see low or negative growth and lower wages over the next several years.

CHAPTER 5: IMPORTANT SKILLS/QUALITIES DATA COLLECTION & EVALUATION

The background research suggested that the likelihood of automation of occupations is driven by which skills make up those jobs rather than the industry or sector that those jobs are in. Ergo, there should be certain skills that are particularly associated with high growth/high wage jobs versus low growth/low wage jobs. The next research objective was to test this hypothesis by analyzing the important skills and qualities required in the high growth/high wage jobs in comparison to the low growth/low wage jobs. In order to accomplish this, web scraping of the U.S. Bureau of Labor Statistics' individual web pages for each occupation was utilized. According to Brown University, "web scraping refers to an automated process that results in the creation of an original dataset by identifying components of a website, and copying pieces of information using a tool (software or programming language) into another file or organized structure for use in a variety of different contexts."[39]

To begin this process, the Google Chrome web browser extension *Web Scraper* offered by webscraper.io was installed. According to the Chrome Web Store, "Web Scraper utilizes a modular structure that is made of selectors, which instructs the scraper on how to traverse the target site and what data to extract. Thanks to this structure, Web Scraper is able to extract information from modern and dynamic websites…"

Creating a "Sitemap" in Web Scraper was the starting point. The homepage for the Occupational Outlook Handbook Occupation Finder (https://www.bls.gov/ooh/occupation-finder.htm) was the "Start URL." The pagination for the 790 entries was dynamic, meaning that when going to the next page of entries, the Uniform Resource Locator (URL) remained the same as the entries being viewed changes. To address this, the first selector was added. The *selector type* was chosen to be “Element click,” the *selector* was each occupation, the *click selector* was the pagination “Next” button, the *click type* was “Click more (click to load more elements. Stops when no new elements with unique text content are found.),” the *click element uniqueness* was “unique CSS Selector,” the “Multiple” box was selected, the *discard initial elements* was set to never discard, and the *delay (ms)* was set to 2000 (Figure 5.1). This allowed for Web Scraper to look through the complete pagination of the 790 occupation entries.

Next, a new selector was created with the pagination selector as the “parent,” meaning that the new selector was the next step in the web scraping process. The *type* was chosen to be “link,” the *selector* was each individual occupation’s webpage link which was hyperlinked from the Occupation Outlook Handbook Occupation Finder, and the “Multiple” box was selected. This instructed the web scraper to open each individual occupation’s webpage.

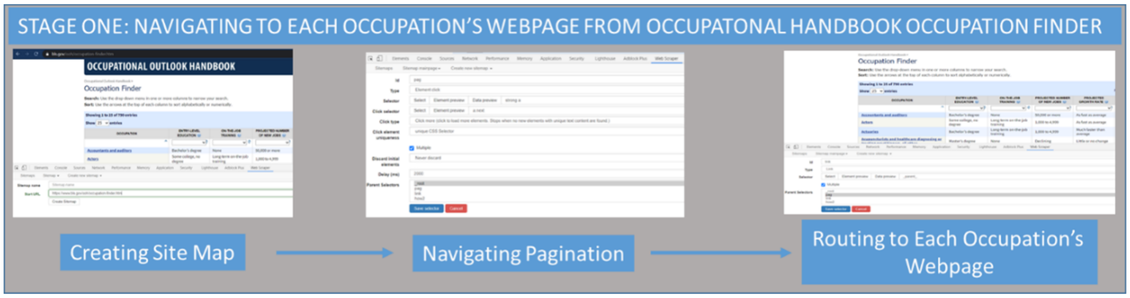

Figure 5.1: Web scraping for important skills and qualities for each occupation Stage One: Navigating to Each Occupation's Webpage from the Occupational Handbook's Occupation Finder workflow diagram. *

*For the figures and tables in this chapter, The Google Chrome web browser extension Web Scraper version 0.5.4 was used. Web Scraping was performed on the U.S. Bureau of Labor Statistics website on October 18, 2020. Georgia Institute of Technology, Atlanta, Georgia.

Then, a new selector was created with the individual occupation's webpage selector as the "parent." The *type* was chosen to be "link," and the *selector* was the "How to Become One" tab on the occupation's webpage (Figure 5.2). This commanded the web scraper to navigate to the "How to Become One" tab on the occupation's webpage.

Penultimate, a new selector was created with the "How to Become One" selector as the "parent." The *type* was selected to be "Text," the *selector* was designated to be the important qualities listed under the "How to Become One" tab, and the "Multiple" box was selected (Figure 5.2). This directed the web scraper to record the important qualities/skills on the webpage. The final step was to run the web scraper (Figure 5.2) which exported the recorded data as a CSV file.

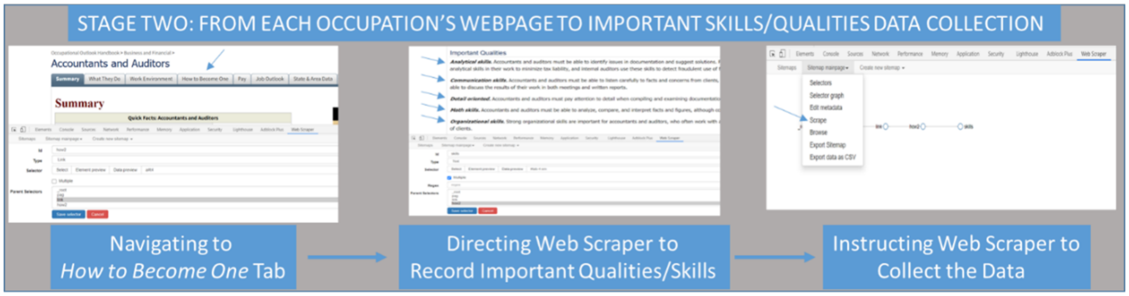

Figure 5.2: Web scraping for important skills and qualities for each occupation Stage Two: From Each Occupation's Webpage to Important Skills/Qualities Data Collection workflow diagram.

Step one in analyzing the web scraped data was to convert the file type from CSV to an Excel Workbook and organize it in a more readable and analyzable structure. The data appeared as a single line of text for each data point scraped. Using Microsoft Excel 2016's the Text to Column function and choosing *Delimited, Tab* (delimiter), and *Text* (column data format), the data was organized into columns including occupation and important skills/qualities. Each important skill/quality was listed in a separate row.

Step two was to filter the data before analysis. It was apparent that the web scraper, for an unknown reason, only scraped data on 552 occupations. Additionally, a number of occupations did not have its own separate webpage. The webpage that these occupations linked to stated, "although employment for hundreds of occupations is covered in detail in the *Occupational Outlook Handbook*, this page presents summary data on additional occupations for which employment projections are prepared but detailed occupational information is not developed." In these cases, the web scraper returned a "null" value. There was a total of 229 occupations where there was not detailed occupational information. Finally, three of the five removed professions from the opportunity values analysis were scraped and did not return a null value. These three were removed from further analysis as they did not have a opportunity value. Encompassing these bounds, 320 occupations, or 40.51% of the total 790 occupations were available for this analysis.

Step three in analyzing the web scraped data was to combine the opportunity values with the web scraped data. In order to accomplish this, the list of occupations and their opportunity values were copy and pasted into a new sheet titled "Vlookup Table" in the Excel Workbook. Then, Microsoft Excel 2016's VLOOKUP function was used to import the opportunity value of the occupation into a new column adjacent to the web scraped data.

Step four was to group the data so that the important skills/qualities for the high growth/high wage jobs occupations could be compared with those of the low growth/low wage occupations. To achieve this, first, Microsoft Excel 2016's Sort function was used to sort the data in order from high growth/high wage jobs occupations to low growth/low wage occupations using the opportunity value as the sort criteria. Second, a frequency table of the opportunity values was created using Microsoft Excel 2016's PivotTable function. This presented how many important skills/qualities were scraped for each opportunity value. In total there were 1960 important skills/qualities scraped. Third, the number of data points scraped for each opportunity value was assessed so that the high growth/high wage jobs and low growth/low wage jobs could be evaluated in the most equivalent approach. A box plot was created using Microsoft Excel 2016 to display the quartiles of the opportunity values of the data points collected. The upper quartile was determined to be opportunity values eleven through fifteen, and the lowest quartile was determined to be opportunity values one through seven. There were 524 data points for opportunity values one through seven (26.73%), and 554 data points for opportunity values eleven through fifteen (28.27%). These two groups were used for the comparison of important skills/qualities.

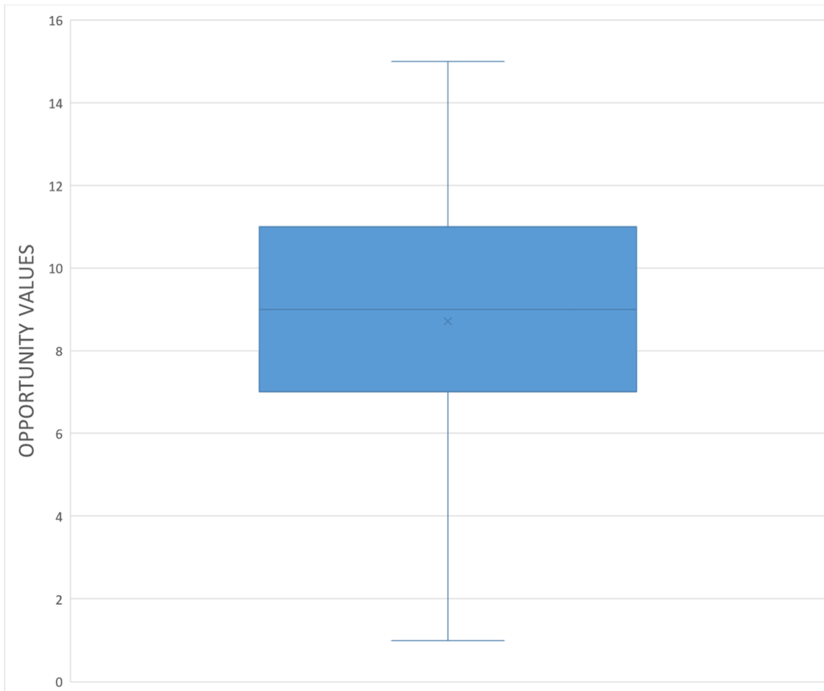

Figure 5.3: Box plot of the opportunity values for the important skills/qualities scraped. Figure created using Microsoft Excel 2016.The Google Chrome web browser extension Web Scraper version 0.5.4 was used to scrape the important skills and qualities for each occupation. Web scraping was performed on the U.S. Bureau of Labor Statistics website on October 18, 2020. Georgia Institute of Technology, Atlanta, Georgia.

Step five was to conduct the comparison of the important skills/qualities for the high growth/high wage jobs occupations with those of the low growth/low wage occupations. To begin, a frequency table of the important skills/qualities for each group was created using Microsoft Excel 2016's PivotTable function. Next, the information was reviewed by the author. Slight variations in spelling (i.e. Decisionmaking skills vs

Decision-making skills) were considered equals with the author erring on the side of caution so as to maintain the integrity of the evaluation. Each group had a total of 79 important skills/qualities associated with them. Those skills/qualities were repeated between one and sixty-two times amongst the other occupations in each group. The top 23 skills/qualities accounted for 82.85% and 80.53% of the total scraped important skills/qualities for opportunity values eleven through fifteen and one through seven respectively. The frequency of these top 23 skills/qualities from each group were calculated as a percentage of their occurrence within the total of the important skills/qualities for each group. This data from the two groups was graphed for comparison (Figure 5.4).

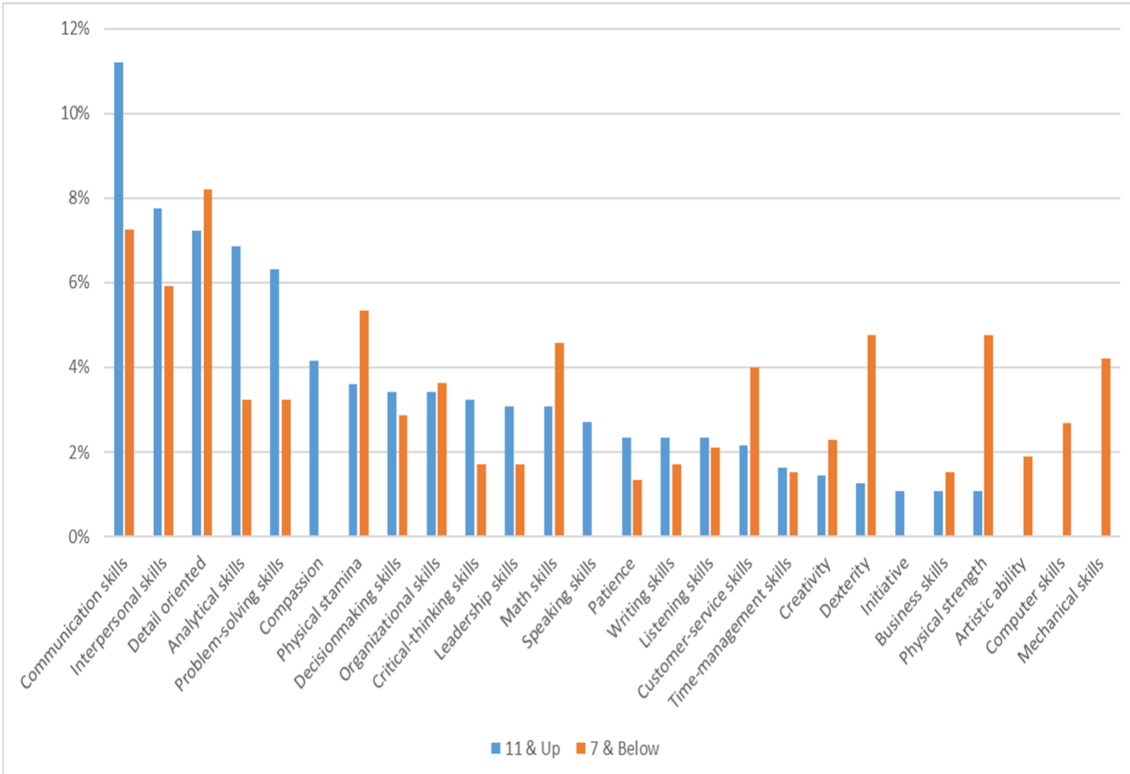

Figure 5.4: Percent frequency of important skills/qualities of all occupations with opportunity values of eleven through fifteen (blue) and one through seven (orange). The Google Chrome web browser extension Web Scraper version 0.5.4 was used to scrape the important skills and qualities for each occupation. Web scraping was performed on the U.S. Bureau of Labor Statistics website on October 18, 2020. Georgia Institute of Technology, Atlanta, Georgia.

Twenty important skills/qualities were repeated in both the most and low growth/low wage job groups. Compassion, initiative, and speaking skills only showed up in the high growth/high wage job group while artistic ability, computer skills, and mechanical skills only showed up in the low growth/low wage job group. Mechanical skills, physical strength, dexterity, computer skills, artistic ability, customer-service skills, physical stamina, and math skills were more prevalent in the low growth/low wage jobs (appeared 1.5% or more than in the high growth/high wage jobs). Compassion, communication skills, analytical skills, problem-solving skills, speaking skills, interpersonal skills, and critical thinking skills were more prevalent in the high growth/high wage jobs (appeared 1.5% or more than in the low growth/low wage jobs).

A Chi-Square Test of Independence was conducted to statistically test the two groups to see whether there is an association between job growth/income and important skills/qualities. First, the expected frequencies for the skills/qualities were calculated in Microsoft Excel 2016 using the formula $\mathrm{E} = \frac{\text{(row total)(column total)}}{\text{total sample size}}$. Next, the p-value was calculated using the CHISQ.DIST.RT (right-tailed probability of the chi-squared distribution) function . The result was a p-value of zero, thus rejecting the null hypothesis that there is not an association between job growth/income and important skills/qualities, and further supporting the alternative hypothesis.

Three (3) of fifty-two (52) of the expected cell counts were below five (5), signifying the need to conduct a Fisher's Exact test. Like the Chi-Square Test of Independence, the Fisher's Exact test whether there is an association between job growth/income and important skills/qualities. It is defined as $p = \frac{(a+b)!(c+d)!(a+c)!(b+d)!}{a!b!c!d!n!}$, where $p =$ P-value, $a, b, c, d =$ values in a contingency table, and $n =$ total frequency. Using the programming language R version 4.1.2 (2021-11-01), p was calculated to be zero, thereby rejecting the null hypothesis in favor of the alternative hypothesis—that there is an association between job growth/income and important skills/qualities.

CHAPTER 6: THE AEC INDUSTRY IN RELATION TO THE TWO TESTED HYPOTHESES

As the final step explored towards the research goal in this investigation, the third objective is to assess the findings of the first two objectives with the occupations that make up the AEC industry specifically. The U.S. Bureau of Labor Statistics publishes the Standard Occupational Classification (SOC) system which, "is used by federal statistical agencies to classify workers and jobs into occupational categories for the purpose of collecting, calculating, analyzing, or disseminating data."[40] Using these codes,[41] the occupations associated with the AEC industry were identified. 17-0000 was the code for Architecture and Engineering Occupations and 47-0000 was the code for Construction and Extraction Occupations. Two occupations, construction and architectural & engineering managers, were included from the code of 11-0000 Management Occupations because they are occupations within the AEC industry. In total 94 occupations (11.9% of all occupations) were designated as being from the AEC industry. Using Microsoft Excel 2016's VLOOKUP, MEAN, MODE, and AVERAGE functions, the 94 AEC industry occupations were compared to all occupations (Table 6.1).

Table 6.1: Table comparing the AEC industry occupations to all occupations. AEC industry occupations were identified using U.S. Bureau of Labor Statistics' SOC codes. Data on the probability of automation is from Frey & Osborne's calculations published in 2016. Opportunity values were calculated previously in this research. Averages were calculated using the assigned values from earlier in this research. Remaining data was obtained from the U.S. Bureau of Labor Statistics website on October 10, 2020. The table was created using Microsoft Excel 2016. Georgia Institute of Technology, Atlanta, Georgia.

	AEC INDUSTRY	ALL OCCUPATIONS
	2019 MEDIAN PAY	
Median	$40,000 to $59,000	$40,000 to $59,000
Mode	$40,000 to $59,000	$40,000 to $59,000
Average	3.43	3.08
	PROJECTED GROWTH RATE	
Median	As fast as average	As fast as average
Mode	Slower than average	Decline
Average	2.69	2.55
	PROJECTED NUMBER OF NEW JOBS	
Median	1,000 to 4,999	1,000 to 4,999
Mode	1,000 to 4,999	Declining
Average	1.72	1.76
	ENTRY-LEVEL EDUCATION	
Median	High school diploma or equivalent	High school diploma or equivalent
Mode	High school diploma or equivalent	High school diploma or equivalent
Average	2.12	2.74
	OPPORTUNITY VALUE	
Median	8	8
Mode	8	10
Average	7.84	7.38
	PROBABILITY OF BEING AUTOMATED	
Median	0.68	0.64
Mode	0.83	0.97
Average	0.55	0.54

From the analysis, the AEC industry is remarkably similar to that of all occupations as a whole. The medians are the same across the board except for a slight deviation within the probability of automation from Frey & Osborne's calculations, with the AEC industry leaning marginally further towards a greater probability of automation when compared to all of the occupations studied. If we take a closer look, the examination shows that the average 2019 median pay, projected growth rate, and opportunity value are all in favor of the AEC industry. The average entry-level education is lower in the AEC industry than the average for all occupations. These findings indicate that careers in the AEC industry may be a good option for those with less education, but there also may be a greater likelihood of automation in the future seeing as occupations that require a high school degree or less are four times as likely to become automated.[14]

Of the 94 AEC industry occupations identified, data was collected using web scraping on 49 (52.13%) of them. Forty-three different important skills/qualities were identified for the AEC industry, and 282 data points were recorded. The results were charted as a percentage within the 23 skills/qualities for opportunity values eleven through fifteen and one through seven from the previous section for comparison. Only three from this latter group did not appear in the AEC industry scraped data. Additionally, the three skills/qualities that did not appear in the original 23 but were amongst the top 18 skills/qualities that accounted for 80.50% of the important skills/qualities scraped for the AEC industry, were also charted to be consistent with charting the important skills/qualities that accounted for approximately 80% from each group. From the analysis, the AEC industry leans heavily towards skills associated with low wage/low growth jobs five times, while leaning heavily towards skills associated with high growth/high wage occupations three times. This finding also signifies that the AEC industry is more susceptible to artificial intelligence and automation because the likelihood of automation of occupations is driven by which skills make up those jobs rather than the industry or sector that those jobs are in, and the AEC industry's skills lean more towards the occupations with low growth and low wages.

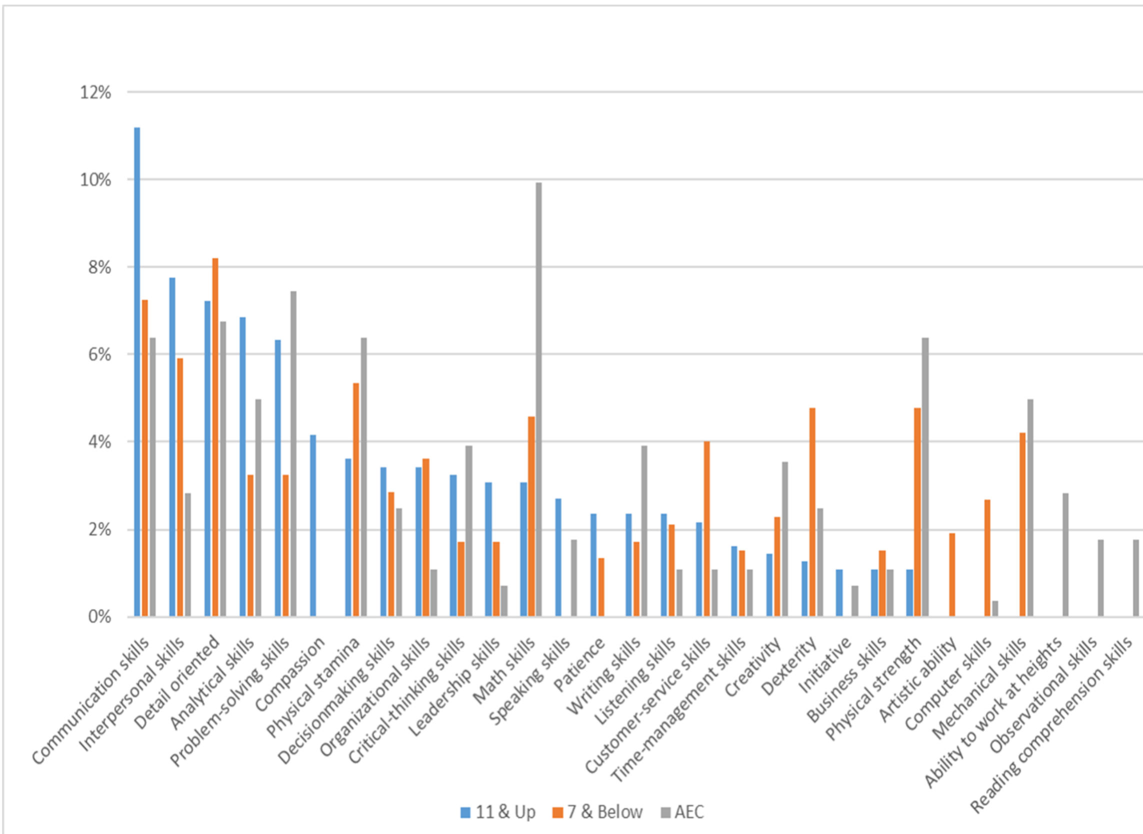

Figure 6.1: Percent frequency of important skills/qualities of all occupations and AEC industry with opportunity values of eleven through fifteen (blue), one through seven (orange), and occupations within the AEC industry. The Google Chrome web browser extension Web Scraper version 0.5.4 was used to scrape the important skills and qualities for each occupation. Web scraping was performed on the U.S. Bureau of Labor Statistics website on October 18, 2020. Georgia Institute of Technology, Atlanta, Georgia.

CHAPTER 7: FUTURE WORK & LIMITATIONS

The purpose of this paper was to look at the AEC industry as a whole; however, the AEC industry is comprised of a variety of professions that will be impacted by Industry 4.0 differently. For example, architects will likely be impacted by Industry 4.0 divergently to how masons will be impacted. A potential area of future research is to conduct more specific analyses on the AEC industry professions, specially examining architecture or mechanical contractors for example, to provide more useful insights into how Industry 4.0 will impact them.

One limitation of this research is that the important skills/qualities identified by the U.S. Bureau of Labor Statistics were general. For example, as a construction manager, communication skills are important, but "the ability to coordinate VDC efforts utilizing BIM Track and BIM 360 Glue," would give more insight in to what specific skills are needed to be successful. An area of future research is to web scrape job postings and/or the LinkedIn profiles to see if more specific skill data is available. Another option is to use a task-based model and work backward to find out what skills are required to complete those tasks. Using factor analysis on the resulting data could reveal hidden patterns and underlying trends. Using cohort and/or cluster analysis, one could use the data to look more granularly, perhaps breaking the AEC industry down into architecture, engineering, and construction individually, or even further into trades (i.e. mechanical, electrical, concrete, etc...). That could shed more specific light on how artificial intelligence is impacting the AEC industry workplace.

Another limitation of this research was how the web scraping program did not scrape each webpage. In future work, utilizing the programming language Python to conduct web scraping would allow for the researcher to have more control to test the web scraping and modify accordingly. Additionally, this research relied heavily on data from the U.S. Bureau of Labor Statistics. Multiple sources of data could minimize potential biases, highlight any discrepancies, and provide a more accurate analysis.

In calculating the occupations' opportunity value, the data groupings established by the U.S. Bureau of Labor Statistics were used. This was done to not overcomplicate the analysis; however, the groups by the BLS were not equal. For instance, for median pay, a "2" was assigned to the $30,000 to $39,000 group and a "3" was assigned to the $40,000 to $59,000 group. The difference in the assigned value for each group is one unit, but the "3" group represents $10,000 more than the "2" group. The author requested the methodology for grouping the data from the BLS, and received the following response via email:[42]

> *…The distributions of pay and occupational growth account for the patterns you're seeing. There's no rigorous method for creating the cutoffs; they're simply round numbers that provided what we considered to be reasonable numbers of occupations in each category. If we made the buckets so that each contained the same number of occupations, the thresholds would be odd, and if we made each bucket cover the same size interval, many of the buckets would contain few occupation…*
>
> *Branch Chief*
>
> *Methods, Systems, and Support Branch*

Division of Occupational Employment Projections

U.S. Bureau of Labor Statistics

Furthermore, projected number of new jobs, projected growth rate, and 2019 median pay were all weighted equally in calculating the opportunity value. In reality, each factor has a different influence on an occupation's risk for automation. Further research and analysis is needed to equally group the data and quantify each factor's weight in order for more accurate opportunity values for the occupations.

Seeing as the AEC Industry is lagging other industries in the adoption of artificial intelligence, another area of future work is to track how other industries are being impacted by their adoption of artificial intelligence and use Monte Carlo simulations to generate models of possible outcomes and those model's probability distributions.

This research focused on the United States of America's economy. A significant area for future research is the global economic shifts that will take place related to Industry 4.0. Certain nations will likely establish dominance in the realm of Industry 4.0, potentially causing labor migration and impacting global politics. On the other hand, less developed countries will see distinct shifts due to the available labor markets and additional factors in those economies. Industry 4.0 is currently and will continue to have substantial impacts on world politics and commerce.

A major topic of discussion in the current environment is how the COVID-19 pandemic will change the way we live and work. With a greater number of people working remotely, will major cities still be a hub for commerce and businesses, or will we see a greater decentralization of the United States' economy? If the economy becomes more decentralized, that will mean that the need for high-rise apartment buildings, offices, higher education buildings, etc. will decrease significantly, thereby impacting the AEC industry. Anecdotal evidence from my industry experience illustrates that we are already seeing shifts in the industry. Mechanical systems are being redesigned to intake more outside air, owners are specifying different hardware and controls to minimize contact, and major projects are being put on hold as owners rethink feasibility and design for projects in the new environment that will emerge after the COVID-19 pandemic. In a survey published by the Associated General Contractors of America (AGC), 30% of firms surveyed responded that they had furloughed terminated employees as a result of the pandemic, and 75% responded that an owner postponed or canceled work.[43, 44] In an industry where the last economic downturn resulted in, "a 19.8% decline in employment, the largest percent decline of any nonfarm industry supersector,"[45] an important area of future research is how artificial intelligence and the post COVID-19 economy will impact the AEC industry workplace.

An important area of future work is how educational institutions can train individuals for the societal and workplace shifts caused by Industry 4.0. Colleges, universities, K-12 schools, employers, and more will need to be able to train workers effectively as the workplace shifts.

CHAPTER 8: CONCLUSION

Artificial intelligence in currently impacting the United States' workplace and is projected in continue uniquely changing our society at a rate to be considered the fourth industrial revolution. Although the AEC industry is behind the curve in implementing both new and existing technologies, it is already seeing the influences of artificial intelligence. Looking specifically at the AEC industry this researched aimed to answer, how the AEC industry workplace could be impacted over the next several years.

The first research objective was to test the hypothesis that jobs more at risk for automation should see low or negative growth and lower wages over the next several years. Using U.S. Bureau of Labor Statistics occupational wage data and growth projections to 2029, a value was created for each occupation. Using Kolmogorov-Smirnov tests, Shapiro-Wilk tests, quantile-quantile (q-q) plots, histograms, and Spearman rank correlation coefficients, the relationship between the opportunity value and probability of automation were evaluated. Multicollinearity was tested for by calculating eigenvalues, condition indices, and variance inflation factors (VIF), and was not found. Statistical significance was found between these two sets of variables, indicating that the first hypothesis is correct.

The second research objective was to test the hypothesis that certain skills are particularly associated with high growth/high wage jobs versus low growth/low wage jobs. The important skills/qualities were web scraped from the individual occupational webpages hosted by the U.S. Bureau of Labor Statistics. The top roughly 80% of important skills/qualities from both groups were assessed and graphed for comparison.

Certain skills/qualities were particularly associated with each group signifying that the second hypothesis is accurate. A Chi-Square Test of Independence and Fisher's Exact test were conducted to verify that there is an association between job growth/income and important skills/qualities. A statistically significant relationship was found.

The third objective was to understand how the findings from the first two objectives relate to the AEC industry. By means of the U.S. Bureau of Labor Statistics publishes the Standard Occupational Classification (SOC) system, the occupations associated with the AEC industry were identified. From there, their opportunity values, growth rate, probability of automation, 2019 median wages, and entry-level education were compared with all occupations as a whole. The findings were that although the AEC industry currently appears to be a good option for the less educated, it has a higher risk of automation based on the data from Frey & Osborne, and the background research predicting that the less educated will be disproportionally impacted by artificial intelligence. Next, the top 80.5% of important skills/qualities that were scraped from occupations within the AEC industry were assessed and graphed with the high growth/high wage and low growth/low wage top approximately 80% important skills/qualities scraped. The finding was that the AEC industry more heavily aligns with the low growth/low wage occupations' skills/qualities versus the high growth/high wage occupations' skills/qualities in a ratio of five to two respectively. This also proposes that the AEC industry is more susceptible to automation and artificial intelligence than other industries based on the background research.

This research is of significance as research into how the AEC industry workplace will be impacted by Industry 4.0 over the next several years was not found in the research background. It has implications into whether young people should choose careers in the AEC industry, what kind of research, development, and workforce training both private and public organizations should invest in, and what skills are required to be successful in near future.

This research was a broad look at the AEC industry and the impacts of artificial intelligence. Future areas of research could use new data sets via web scraping and other sources, Monte Carlo simulations, cohort analysis, and cluster analysis to make more specific forecasts. Additionally, in this day and age, how COVID-19 has changed the United States' economy needs to be researched to accurately envisage the future of the AEC workplace.

APPENDIX A. BASIC STATISTICS FOR OCCUPATIONS' OPPORTUNITY VALUES, RELATED VARIABLES, AND FREY & OSBORNE'S DATA

Statistics

		FreyOsborne	NewJobs	Growth	MedianSalary	OccupationOV
N	Valid	640	640	640	640	640
	Missing	0	0	0	0	0
Mean		.5368	1.7031	2.4047	3.0313	7.1391
Std. Error of Mean		.01464	.06215	.07555	.04828	.14541
Median		.6400	1.0000	3.0000	3.0000	8.0000
Mode		.97	.00	.00	3.00	3.00
Std. Deviation		.37047	1.57225	1.91125	1.22147	3.67852
Variance		.137	2.472	3.653	1.492	13.531
Skewness		-.293	.518	-.058	.080	-.047
Std. Error of Skewness		.097	.097	.097	.097	.097
Kurtosis		-1.553	-.969	-1.476	-.842	-1.164
Std. Error of Kurtosis		.193	.193	.193	.193	.193
Range		.99	5.00	5.00	4.00	14.00
Minimum		.00	.00	.00	1.00	1.00
Maximum		.99	5.00	5.00	5.00	15.00
Sum		343.56	1090.00	1539.00	1940.00	4569.00

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