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Distinguishing the Job Market Across Aerospace and Aviation: A Natural Language Processing Approach

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This study dives into the intricate landscape of the aerospace and aviation job market. While these two markets are often conflated as being similar, if not the same, we propose that the differences are important to recent graduates of educational institutions and career programs. The research utilized a custom-written Natural Language Processing (NLP) software tool to distinguish the differences in 6,000 job offerings between the two industries with the hope of illuminating nuances to those in positions involved in placing professionals into careers. This research not only reveals the dynamic employment landscape of aerospace and aviation but also highlights the power of NLP in more clearly discerning emerging trends in job data.

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Although the U.S. Aerospace and Aviation industries are known to be highly bifurcated from those closely related to the field (Vasigh & Gorjidooz, 2016), they are largely seen as one singular entity to human resource and human capital professionals in the job market. In reality, the division between the two exists in two primary domains: the first being developmental (i.e., aerospace) and the second being operational (i.e., aviation). These divisions have a direct impact not only on the labor force skills required to operate within these specific industrial sectors but also have an impact on the evolvement of where these sectors are located (Rochon, 2011). For example, the aerospace sector is predominantly located on the Atlantic and Pacific Seaboard of the United States (Dancy, 2017), with more of the manufacturing portion of that workforce located on the Pacific Seaboard (Platzer, 2009). However, there are areas in the country that have been successful in gaining traction with Aerospace and Aviation manufacturing jobs, like Texas, Kansas, and New Mexico (Chang, 2020; Yazici & Tiwari, 2021).

While looking somewhat similar in name, each industry sector is distinctly different. Aviation is mainly focused on activities surrounding mechanical flight within the troposphere and stratosphere (Torenbeek & Wittenberg, 2009). This includes aircraft that are fixed-wing, rotary-wing, morphable wings, wing-less lifting bodies, and lighter-than-air craft such as hot air balloons and airships (Vinh, 1993). The newer field of urban air mobility (also known as Advanced Air Mobility) would also be included in the aviation sector (Reiche et al., 2021). In contrast, the aerospace sector has activities primarily surrounding mechanical flight within the troposphere, stratosphere, mesosphere, thermosphere, exosphere, and outer space (Anderson et al., 2015; Sirieys, 2022; Suthagar et al., 2022). In addition to aircraft, aerospace-focused organizations design and operate "mesospheric-plus vehicles" (i.e., rockets, missiles, spacecraft, satellites, probes, rovers, etc.) (Tewari, 2011).

The researchers conducted a systematic literature review in aviation and aerospace journals and found that existing research focused on the combined aspects of the aerospace and aviation industries without considering the multiple facets of each that make them unique for the workforce and job labor markets. For example, Lappas & Kourousis (2016) focused on new skills in the aerospace and aviation industries without marking differential aspects between the two. Additionally, in Rochon (2011), the focus of aerospace and aviation workforce strategy contained no differentiation of the terminology.

Our research goal is to determine if there can be clear delineations between the aerospace and aviation industries when examining job data from the employment market. This would be useful and timely for institutions of higher learning and educational programs that offer students career services to more directly help their alumni seek the most applicable jobs to their careers. Those involved in aviation research understand that these two industries are highly specialized with unique workforce needs (Bedialauneta et al., 2020). However, this research also seeks to further clarify the special workforce needs of those who would be involved in assisting graduates and future employees with their careers, such as advisors, career services professionals, and human resource departments of the company they ultimately choose. While some of our older notions of the workforce may remain the same, our goal for this research is focused on illustrating emergent trends regarding a) job title classifications between the aviation and aerospace sectors, b) classifying the human capital skills, and c) quantifying the demand for labor skills across these two industrial sector segments.

Methodology

This research is based on computational grounded theory. Traditional grounded theory is a research method designed to allow for the analysis of qualitative information, arriving at an underlying emergent theory via the categorization of information via unstructured phenomenon (Nelson, 2020). By contrast, computational grounded theory is a research method designed to quantitatively analyze qualitative information, arriving at an underlying emergent theory using a focused data-driven categorization of unstructured phenomenon (Glaser & Strauss, 2017).

As part of the computational grounded theory process, our unstructured data sets were codified by our research team and analyzed using a natural language processing (NLP) engine that we developed in-house. NLP uses continuous sequences of words or symbols called N-grams. These N-grams are processed through a systematic treatment, resulting in the breaking down of text into chunks of words (Guo et al., 2021). After the text has been converted into N-grams, it becomes useful to start categorizing relevant information using NLP (Dreisbach et al., 2019). These chunks of text are especially useful when planning on using word frequency models (Guo et al., 2021)

Each job record was labeled as being either 'aerospace' or 'aviation' based on our researchers' review of the company's predominant mode of business. For example, when coding Lockheed Martin, it is a company noted for primarily being an aerospace-based company; a company like 'United Airlines' would be coded as being an aviation-based company. This is known as structure augmentation (also known as substructure augmentation); in our case, this form of data augmentation divides the research data into two data tree structures (i.e., aerospace and aviation). This structural data augmentation allows us to perform comparative NLP tasks such as text parsing, textual classification, and comparative token analysis (Shi et al., 2021).

Data Sources

Our data sources were then organized into two main categories: *market data* and *job data*. Market data is predominantly economic and financial in nature, and we leveraged two sources: Economic Modeling Specialists International and Fidelity Investments. These data sources were used to determine macro-level industrial segmentation metrics such as business sectors, market capitalization (market caps), sector performance, and industry growth. A visualization is presented in Figure 1 for market data and Figure 2 for job data.

Figure 1
Market Data

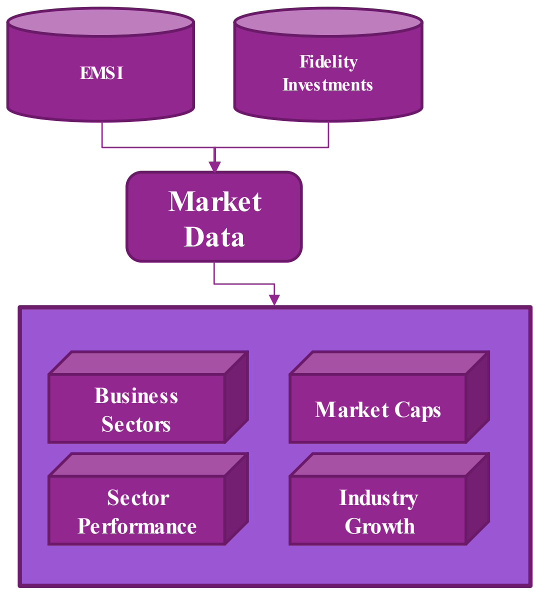
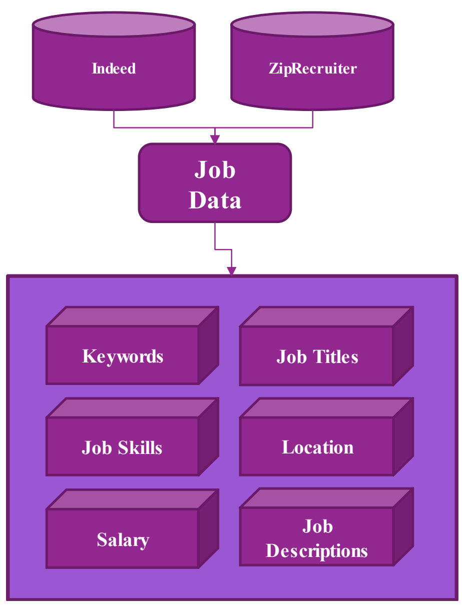


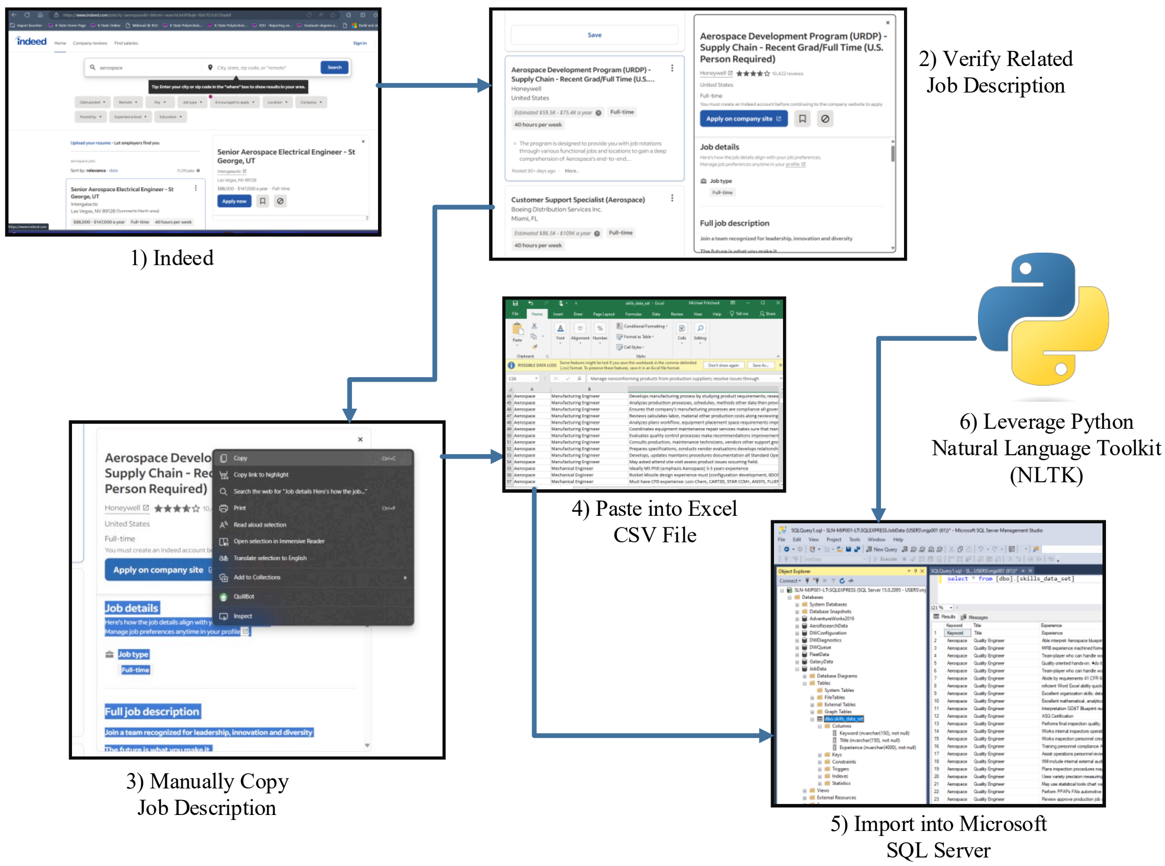
Figure 2
Job Data



Our job data comprises our secondary data source. This is composed of unstructured job board data that was manually scraped from the Indeed and ZipRecruiter job sites. Both websites have been used with success as a source of professional job data in defining job market demands (Eberts, 2023; Wang, 2020). To gather this data, we manually employed a systematic process between. First, the researchers searched ziprecruiter.com and indeed.com for all available aerospace job postings between May and June of 2021. This search range was substantiated by a report from Brazen (2015) that found that 43% of job openings are filled during the first 30 days, and conversely, 57% of job postings may still be active after a month. For each job posting, we manually copied and pasted the web page that contained all descriptors of the job (keywords, employer name, job titles, job skills, location, salary, and job description) into a .csv file. We repeated this process for aviation job postings. Next, we imported the raw text data into our Natural Language Processing engine. A visualization representation of this process is presented in Figure 3.

Figure 3

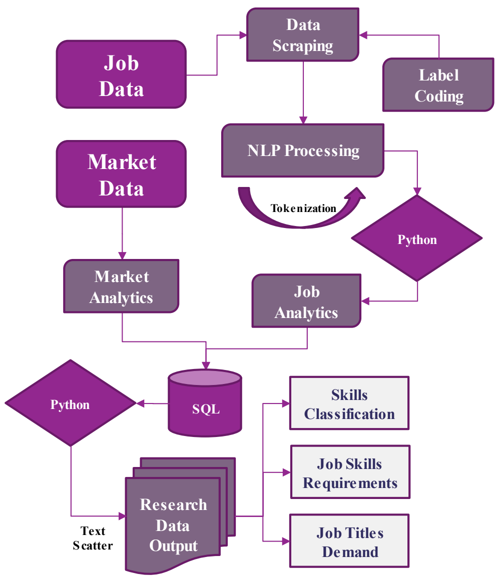
Initial Scraping of Data into Python for NLP



Data Process Model

While the market data provides macro-level market analysis, it does not by itself provide details regarding the job title classification between the aviation and aerospace sectors, the classification of human capital skills, or the quantification of labor demands across these two industrial sector segments. In this regard, we created the job data dataset to provide detailed insights into these three areas. A visualization is presented in Figure 4.

Figure 4
Data Process Model



Python was used to build our natural language processing engine. Python libraries included within the NLP engine include pyodbc, scattertext, nltk, pandas, and spacy. A SQL Server database was used to store and structure the job data. Python was also used to build the textual scatter plots seen in the results.

After completing our data process model (See Figure 3. Data Process Model), we were able to clean and distill 6,034 data samples across fifteen different organizations. A visualization of these companies and sample counts are presented in Table 1.

Table 1
Job Data Table (n=6,034)

Code	Organizations	Sample Count	Market Cap (Billion)
Aerospace	Lockheed Martin	2,841	$98
Aerospace	Honeywell	1,370	$144
Aviation	Textron	590	$16
Aerospace	Raytheon-Collins Aerospace	477	$130
Aviation	Alaska/Horizon	221	$7
Aviation	Delta	85	$25
Aviation	Spirit AeroSystems	78	$4
Aviation	Frontier	72	$3
Aviation	Flight Safety International	71	$1
Aviation	American Airlines	62	$11
Aviation	Bombardier	53	$3
Aviation	United Airlines	38	$14
Aviation	SkyWest Airlines	37	$2
Aviation	Mesa Airlines	31	$0.2
Aviation	Republic Airways	8	$0.0

In collecting the data, it was evident early on that the demand for aerospace jobs far surpassed that of aviation jobs. The demand difference was such that in our data collection efforts, we noticed early on a striking size differential between the aviation data tree and the aerospace data tree. A visualization of the two areas is presented in Table 2.

Table 2
Sector Data Tree Counts

Data Tree	Sample Count
Aerospace	4,688
Aviation	1,346

Using Fidelity Investments, we captured high-level macro metrics. Our data consists of domestic U.S.-based organizations that are publicly traded, where the industrial financial market data was collected and grouped according to industry classification and associated segments within the "industrials" sector (Fidelity Investments, 2021). Additionally, from a data sampling perspective, the individual tree sizes are more than twice what we needed to perform natural language processing-related tasks (Figueroa et al., 2012). The macro-level market data was used as a labor demand control group (i.e., when comparing the Sector Data Trees at a micro-level, we would get different results at a macro-level). While we can analyze skills within each data tree individually, we introduced a data ratio metric. This ratio was used as a control mechanism to a) standardize the data frames and b) enhance our analytical confidence when contrasting the labor demand differences between these two data trees.

As an industrial complex, the industry's sector market cap metric should, in theory, approximate the labor demand differences in the lower-level job data. A visualization of the market data is presented in Table 3. While there might be some slight variations, we should not see drastic labor demand deviations between the market data and the job data. As shown in Table 3, the market cap found in this study is within the data range of the overall market cap for each industry.

Table 3
Sector Market Cap

Sector	Market Cap Industry Total (in Billions)	Market Cap Within Study (in Billions)
Aerospace	$680	$372
Aviation	$192	$86

Results

The skills requirements within the job data exhibited a clear delineation of labor skill demands between aerospace and aviation-coded job descriptions. The types of jobs within the job data illustrated a market demand for labor largely in keeping with the higher-level market capitalization metrics found within the market data dataset. In analyzing our proposed data control mechanism, we found the sector data tree ratios to be similar. A visualization of the data is presented in Table 4.

Table 4
Data Control Group

Market Data	**Sector**	**Market Cap (In Billions)**	**680 / 872 = 77.98%**
	Aerospace	$680	
	Aviation	$192	
	Total	**$872**	
Job Data	**Data Tree**	**Sample Count**	**4688 / 6034 = 77.69%**
	Aerospace	4688	
	Aviation	1346	
	Total	**6034**	

The similarities are notable since, during our data collection process, we noted the need for more aviation data to help augment the job data disparity we were seeing in the data collection process. As it turns out, the job data disparity largely mirrors the macro market data metrics, and upon further review, we determined that our data sampling process remained intact.

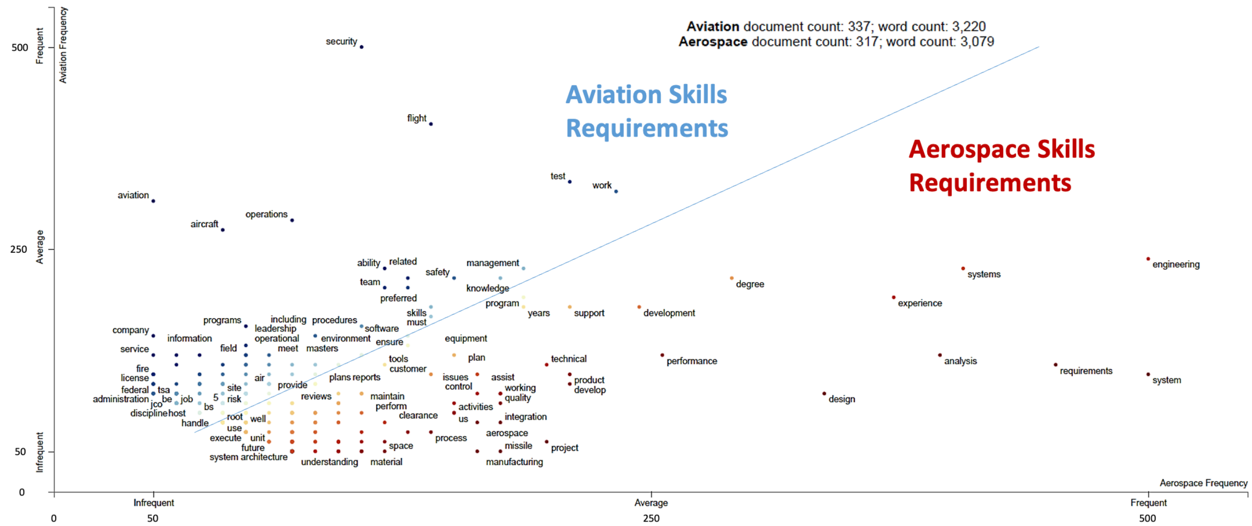
Market Data

The total market capitalization of all firms in the industrial sector is roughly $5.21 Trillion (USD). The associated industries within the industrial sector specific to this research were "aerospace and defense" and "airlines." Additional sectors were captured as part of this research; however, our analysis was strictly focused on a standard data tree comparison between the two datasets (i.e., clearly defined aviation companies and clearly defined aerospace companies). The effects of COVID-19 really had a strong impact on the evaluated market sectors. Aerospace saw a decline of -21% growth from 2019 to 2020, with airlines seeing a decline of -17% over this same time period.

Job Data

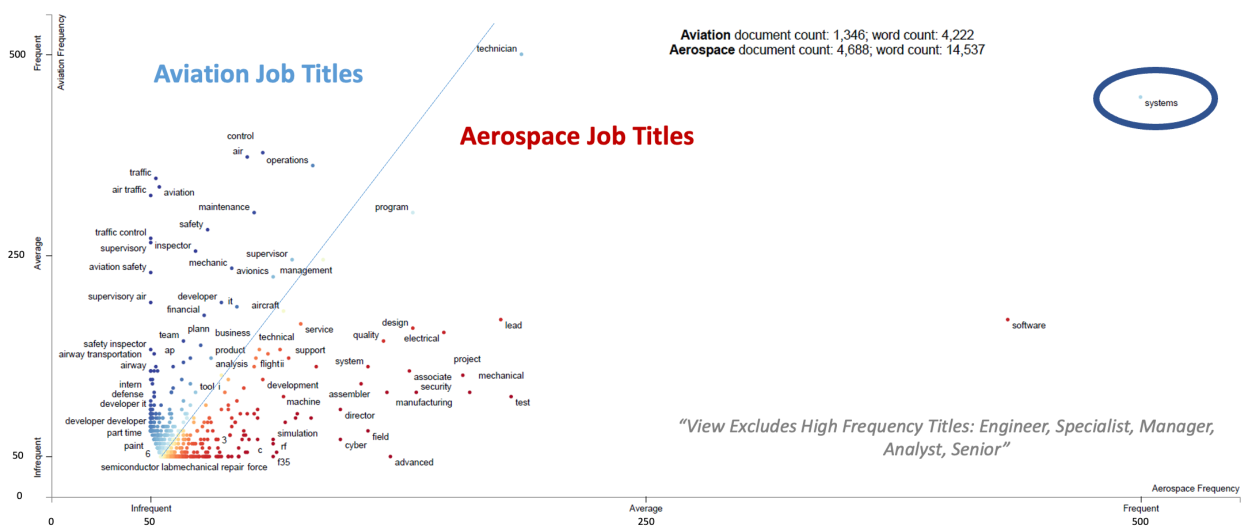
The skills requirements text scatter data illustrates the variety of skills demanded by their respective industry sector assignment. The top skill requirements within the aerospace data tree are engineering, systems, analysis, and design. The top skill requirements within the aviation data tree are as follows: aviation, aircraft, operations, and security. The skills requirements text scatter does not illustrate a demand perspective. A skills requirement scatter plot visualization is presented in Figure 5.

Figure 5
Skills Requirements Text Scatter Plot



It merely illustrates the skill breakdown between these two segments. However, a jobs demand perspective was included and illustrates the labor demand between aerospace and aviation. A jobs demand scatter plot visualization is presented in Figure 6.

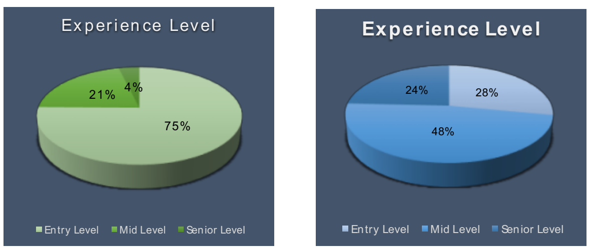
Figure 6
Job Titles Demand Scatter Plot



High-frequency terms such as engineer, specialist, manager, analyst, and senior illustrated a consistent theme within the data set that the demand for mid-to-senior level STEM-based jobs (Science, Technology, Engineering, and Mathematics) was a top priority in both sectors, yet, in higher demand within the aerospace sector. The demand for these mid-to-senior level jobs was so high that our initial job title scatter text was unreadable due to the high-volume frequency counts producing far-flung outliers that had the effect of shrinking the main scatter text to unreadable proportions. Thus, engineers, specialists, managers, analysts, and seniors were hidden so as to expand the scatter text view. In this view, we can see job titles that contain "systems" and "software" comprise not only the top two job spots in the aerospace sector but also the top job spots overall. Additionally, the job data illustrates an interesting trend regarding experience level. The aviation sector has a higher tolerance for hiring entry-level personnel; by contrast, the aerospace sector has a much lower tolerance for entry-level personnel. A visualization is presented in Figure 7.

Figure 7
Experience Level

Aerospace Sector Aviation Sector



Lastly, pay tends to be 11% higher on average in the aerospace sector versus the aviation sector. A visualization is presented in Figure 8.

Figure 8
Pay Scales

Aerospace Sector Aviation Sector

Discussion

When discussing the human capital requirements as it relates to the aerospace or aviation sectors, often the conversation will focus on the workforce demand of 'pilots' and 'mechanics' (Caraway, 2020; Crouch, 2020; Lutte, 2018). While there has been a lowered demand for pilots and mechanics in the aviation sector workforce pipeline prior to COVID-19 (Bidaisee, 2021), this lowered demand for other skills was not exhibited across both the aerospace and aviation sectors. Systems thinking and systems-based skillsets dominated the data conversation within this research. Skills such as system analysis, systems architecture, systems design, and systems engineering all play a large part in this field. We believe that being able to think holistically – at multiple scales, both large and small – is something that comes with experience, and we see the demand for not only experience in the aerospace sector but we also see a high demand for systems-based skillsets. Aerospace companies see the value in "sustainability awareness," and much of their ability to be successful depends on their ability to be systems-focused (Scurati et al., 2020).

While the aviation sector has largely maintained its need for pilots, mechanics, and associated support personnel, the staffing needs of the aerospace industry are being progressively driven by integrative needs in science, technology, and engineering. Increasingly, this is leading many aerospace-based organizations towards the acquisition of 'systems-oriented' staffing requirements. This research helps to better align higher educational institutions with the current industrial staffing complexities within the broader aerospace sector. This research also highlights areas of demand that extend beyond pilots, mechanics, and engineers. For example, we found an increasing demand for artificial intelligence, cyber systems, and cyber security professionals, regardless of the industrial background. This highlights national emergent trends in this area seen across all industrial sectors outside of aerospace and aviation (Schuster & Wu, 2018).

Limitations

The market data discussed in section 2.1 was inconsistent in its segmentation, often creating overlaps where aerospace companies were tagged as being aviation companies and vice versa. This limited our ability to use the market data for detailed research at the micro level (i.e., its usage was predominantly relegated to macro-level insights).

In regard to the job data capture process, we were unable to gain access to their respective API frameworks. As members of a research institution and not a recruiting institution, our organization was considered "out of the market" to warrant access to their respective API frameworks despite our attempts. In light of this limitation, we were still able to capture a significant number of data samples using a manual approach: 654 skill-focused samples and 6,034 title-focused samples.

The "air freight and logistics" industrial sector was also evaluated as part of this research, but it was removed as we did not capture the market data at the same level as the job data regarding this metric. In other words, it was removed from our analysis to keep the comparison between job data and market data equal. We did not include the air freight sector in our analysis as we felt it was important to keep a cleaner delineation of job data and market data equal amongst the industrial sector segments. The air freight industrial sector itself is also part of the supply chain industry, which brings with it additional research parameters requiring a detailed expense analysis to separate out aviation expense as a ratio to market capitalization across all major air freight organizations. While outside the scope of this research, it is part of a future research agenda, especially as it relates to a global perspective of market and labor demand.

Lastly, our data capture was relegated to domestic U.S.-based publicly traded companies. While we recognize that there are significant aviation and aerospace labor demands in the government sector (i.e., NOAA, FAA, and DoD), we excluded them from this research to keep our research commercially focused. Additionally, we did not incorporate private entities. Private entities have more volatile valuations, making the prospect of including private entities more difficult. However, as more predominant space-based companies turn public, a new space-based data tree will be created for inclusion in future research.

The researchers plan for future research into NLP and job and market data by including more variables such as how long positions are posted, how quickly positions are filled, and other quantitative data. These concepts would further enhance our understanding of the labor demand in these two industries.

Conclusions

Our goal for this research in the aviation and aerospace industries focused on a) differentiating job title classifications, b) classifying the human capital skills, and c) quantifying the demand for labor skills across these two industrial sector segments.

Towards our first research goals, the research data collected in this study showed a differentiation between job classifications and human capital skills between the two industries. Prior to this research, we inherently understood job title classifications such as pilots and mechanics are predominantly in the aviation sector, whereas scientists, technologists, engineers, and developers are predominantly in the aerospace sector, with varying levels of overlap. Our research shows through the use of NLP the differences between these two sectors in more nuanced ways, such as differences in job titles, skills, pay scale, and entry-level hiring tolerability.

Towards our research goal c, quantifying the demand for labor skills, we know that demand as a function of market capitalization is well documented (Aghion et al., 2022; Solow, 1964). As a company grows in market capitalization, so does its demand for labor to meet that increased market share that the company captures (Solow, 1964). As the capital stock rises, the production function moves upward, leading to a simultaneous outward shift of the labor demand curve. This results in the hiring of more workers (Solow, 1964).

From a research perspective, the ratio metrics used as a data control were effective in this research. Using the market capitalization as a proxy control group for labor demand was an unexpected find in the research output. Future research may indicate that this style of analysis has the potential to generalize into other industrial sector analyses. We do suspect that the data tree ratio will change given the lens in use (i.e., global vs domestic, airline vs air freight, air freight vs aerospace). For example, the global aerospace market capitalization stands at $873 billion dollars; the global aviation market capitalization is currently $327 billion dollars. The difference between these two global segments currently sits at 72.75%. We hypothesize that this macro-level ratio would be somewhat consistent at the micro-level. We speculate that the job data demand ratio could swing +/- 2% of the market data metric. Of course, wider swings in this metric are possible, and in these cases, this may indicate increased market and labor volatility.

For future research, we hypothesize that the data tree ratio itself (micro-level, job data) would have only slight variation when compared to the macro-level, market data dataset (i.e., the ratio may change, but the ratio between the job data and the market data should remain somewhat equal). However, we speculate that there is another phenomenon at play regarding the directionality of an organization's market capitalization. As an example, if a company goes through market pressure via the loss of business, it will feel downward decapitalization (selling of public shares on the open market). This phenomenon will occur rapidly on the open market before it has a downward-facing effect on the labor within the organization, which may indicate why the labor job data ratio metric (77.69%) lags behind the market data ratio metric (77.98%) within our data. While additional research is required, we speculate that an inversion of this metric, where the job data ratio leads the market data ratio, may indicate a given job sector is becoming increasingly centralized (i.e., a broader movement of aviation jobs transitioning into the aerospace sector faster than the capitalization structure of the respective organizations in that sector).

In addition, higher education institutions should see that the data can be sensitized to educational frameworks for the demands of their respective industries. For example, aviation-based and aerospace-based education programs of higher learning should evaluate and understand that the labor force requirements are more nuanced between aviation (operation-oriented entities) and aerospace (development-oriented entities).

Using computational grounded theory and data structure augmentation proved to be useful for this style of research, and we look forward to expanding this research line further. Our primary goals for this research have illustrated various emergent trends regarding the skills classification between the aviation and aerospace sectors as well as the human capital requirements and labor demand movements within and across these two sectors.

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