The Impact of Natural Language Processing on Streamlined Operations in American Aerospace Manufacturing: Enhancing Productivity

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1. Introduction

1.1. Background and Significance

The impact of the COVID-19 pandemic, extreme weather events, international conflicts, and global trade tensions have combined to present America's aerospace manufacturing supply chains with unprecedented challenges. Aerospace customers are demanding greater efforts to safeguard, align, and seek new sources for material, parts, subassemblies, and assemblies as supply chains worldwide have eroded due to various geopolitical, weather, and pandemic causes. A serious shortage of workforce talent on the shop floor level has occurred, a critical issue due to the unique skill requirements in the aerospace manufacturing industry. Shop floor talent is crucial to the successful operational performance of manufacturing businesses. Natural Language Processing (NLP) is a form of AI that affords many opportunities to improve workforce performance and retention. Productivity implications for U.S. aerospace manufacturing are profound.

Manufacturing challenges are found on the shop floor level on a day-to-day basis. Manufacturing challenges affect productivity, worker performance, worker retention, product quality, and many other business key performance metrics. These challenges arise fully in the human conversation space, either audio or written text. It is during human conversation interaction in which the manufacturing challenge discussions are created and exist. Manufacturing challenges are usually situated in hi-tech environments of complex machinery, tools, and software. This hi-tech environment makes it difficult to onboard new talents beyond just needing to teach the job responsibilities and key performance metrics. There are many implicit and undocumented knowledge and experiences that lie in the seasoned talents of the current workforce. A shared communication gap can emerge between experienced workforce talent and new workforce talent. This situation is known in the literature as a team of "know-that" and "know-how" individuals. Good manufacturing challenges knowledge and experiences are usually told or learned via informal or unstructured human conversation. Extracting and documenting manufacturing challenges knowledge or lessons from past events provides concordance for new rising talents to learn what to think and what to do in case a similar event occurs again.

There is a wide range of AI technologies that can assist human conversation. This paper will focus on Medium Complexity Natural Language Processing (NLP) domain solutions and applications to assist the aerospace domain in addressing workforce talent challenges in the manufacturing conversation space. There are many NLP methodologies that can convert audio conversation to structured knowledge for storage and retrieval. NLP can analyze stored conversation knowledge and pinpoint important issues and occurrence patterns. NLP application systems can assist workers in the conversation and best practice exploration in real-time, among others. Using the aerospace domain terminology, definitions, and initial assumptions, it will explore the potential manufacturing operational performance uplift due to the introduction of diverse NLP solutions. The proposed direction is unique from the point that it contains concrete insights into the manufacturing shop floor level. It is unique from the angle that it investigates the productivity implications for a whole sector, the U.S. aerospace manufacturing domain.

1.2. Research Objectives

This study aims to analyze the impact of NLP methodology application on the aerospace manufacturing sector, with a focus on productivity uplift. This analysis takes a top-down approach, beginning with the U.S. economy's reliance on the aerospace manufacturing sector. Subsequently, the sector's performance is reviewed, along with its specific workforce talent challenges. Thereafter, the Medium Complexity NLP methods are described, and the productivity uplift opportunities are examined in detail. Finally, the sector uplift calculations and results are presented.

1.1. Background and Significance

The aerospace manufacturing sector plays a crucial role in the economy and national security of every country, especially in the United States. Its manufacturers have to adhere to strict standards in the design, fabrication, and assembly of aviation components. These standards are enforced by the Federal Aviation Administration (FAA) and the European Union Aviation Safety Agency (EASA) to ensure aviation safety and airworthiness of commercial aircraft. A large number of ever-growing and increasingly complex standards are available in the form of thousands of documents, which are extremely expensive in terms of time and money to analyze and comply with. Deep Natural Language Processing models are employed to automatically analyze regulatory documents in the context of aviation engineering, with the aim of developing tools that enhance the compliance process and, therefore, streamline usual operations in aerospace manufacturing.

The exponential growth of regulatory standards poses a significant challenge for American aerospace manufacturers in designing, writing, and submitting certification documents for complex aviation products. All changes to aviation products need to be analyzed for regulatory impact. Relevant standards must be identified, with key requirements extracted and arguments to show compliance developed. This process is extremely tedious and time-consuming, especially for large-scale complex systems like Commercial Off-The-Shelf (COTS) electronic systems.

The main goal is to investigate the use of Deep Natural Language Processing tools that exploit state-of-the-art language models to support compliance with regulatory documents in aerospace applications. Automatic question answering on regulatory documents is addressed as a first inquiry, building upon existing question answering techniques. These are typically based on a retrieval step to select the document or document passage that likely contains the answer, followed by a skip step that uses patterns or the context surrounding an answer candidate to extract it. The performance of existing methods is improved with respect to interpretability and precision through a hybrid approach that combines domain-dependent keyword-based filtering with an existing architecture based on transformer neural networks. This hybrid approach is shown to be particularly effective for complying with large sets of carefully selected relevant standards.

1.2. Research Objectives

To research and explore the approach of American aerospace manufacturers in operating with streamlined processes in terms of manufacturing speed, precision, and product traceability through the use of Natural Language Processing and Artificial Intelligence. With this aim, an extensive online data collection will be performed on a manufacturer using Natural Language

Processing to provide a more insightful account of its current competitive advantages in terms of time efficiency, quality consistency, and transparency in the manufacturing process. It will also examine how these improvements enhance productivity, such as the immediate provision of manufacturing status to end-users, prevention of human error and unnecessary asset waste by adhering to standards and documents, and control of product data and manufacturing stages. Finally, an evaluation of the most recent advances in Natural Language Processing and Artificial Intelligence technology and products will be conducted to assess the current competitive edge of the manufacturer being researched. This evaluation will determine whether the current approach should be maintained or if new technology should be adopted. To focus the research, a limit window of no older than 5 years will be established for the collection of information.

2. Fundamentals of Natural Language Processing

The general overview of natural language processing (NLP) is presented here. It attempts to provide the reader with the fundamental understanding of the subject matter: what NLP is, an overview of the basic strategies utilized in NLP, and why NLP is desirable [1]. NLP deals with the understanding and generation of natural languages by computers. A primary concern of NLP is the effort to find methods and mechanisms which will allow computers to understand and respond to the natural, colloquial, spoken English language (or any human language). NLP also requires the ability to understand a sentence's word order and structure, to recognize idioms and metaphors, and to analyze other linguistic and semantic subtleties more subtle than previous sentiment polarity or reasoning approaches [2]. Basically, the goal of NLP research is to implement within computers the ability to understand (or even converse in) a normal human language. Such an emotion-responsive companion conversational computer could retrieve and analyze pertinent information from a wide variety of sources, recognize the implications and significance of that information, retain that knowledge, and 'learn' from the interaction. Furthermore, such a computer could sense human emotional states through voice and language analysis alone and reproduce corresponding emotional expressions. NLP attempts to explore the nature of man-made machines which can replicate many of the characteristics so peculiarly human.

2.1. Definition and Overview

Natural Language Processing (NLP), a subfield of artificial intelligence (AI), focuses on the interaction between computers and humans through natural language. As a complex interplay between linguistics and computer science, it aims to enable machines to comprehend, interpret, and generate human language in a way that is both meaningful and useful. NLP systems are designed to facilitate the processing of text and speech, employing a combination of computational linguistics and machine learning techniques to analyze, understand, and produce human language. The primary goal of NLP is to bridge the gap between the human linguistic communication system and the numerical, logical, and mathematical computer communication system.

NLP encompasses a wide range of tasks and applications, from simple text processing to complex understanding and generation of language. Text-based NLP tasks can be classified into two categories: NLP formats that deal with raw, unstructured texts and require complex understanding or generation of language; and non-NLP formats that, although text-based, do not require complex processing or understanding of the language. Speech-based NLP tasks involve the processing of spoken data in various degrees and stages of understanding. They may start as non-NLP formats requiring transcriptions or modifications of the input digital signals, followed by simple text-based NLP processing. Spoken data may also be entered in a fully processed and understood form, as in automatic speech recognition systems.

The ongoing expansion of new technologies, economic globalization, and color revolutions have led to an increase in dual efforts on creating a more secure, just, and equitable world. Digital and intelligent society build a tremendous need for a better understanding of the world around and wider, more effective, and faster dissemination of human knowledge. This, in turn, expresses an issue for better understanding, generation, and manipulation of various natural languages, which are diverse and linguistically dissimilar but must be treated equally and rapidly. On the underlying technologies' side, the new era poses fresh challenges and affords new opportunities for their evolution and development. There is a clear motivation for more research and investments in NLP.

2.2. Key Techniques and Applications

The actual techniques of NLP may be less important to the reader's understanding of what is possible. The heart of NLP is variable-complexity, operations of linguistic automation that build up higher-level information and understanding from lower-level structures. This, it is felt, need not be technical [1]. To understand phrases that would otherwise be syntactic strings like, "vegetable fowl," one might need to carry out all of the complex linguistic and world knowledge operations in this proposal in the opposite direction: starting from expected knowledge in order to success with word forms and a surface structure string. But NLP is not simply about understanding syntactic strings. It is increasingly apparent that NLP cannot be restricted to the increasingly ill-defined domain of intelligence that is no more than language-driven. There is a need to look at new ways to understand more general questions of language technology and linguistic understanding.

The aim of this section is to look at a number of the many real-world applications of NLP which might give this sense [3]. The applications examined here are by no means the only or even the most important ones, in many ways they are all-or-nothing approaches concerned with monolithic applications. NLP applications are already in operation and have the power to transform quite the efficiency with which tasks as diverse as translations of documents, banking and knowing about the weather and/or last night's football matches are carried out. These can be much larger projects with potentially far greater information handling capabilities.

3. Current Applications in Aerospace Manufacturing

In North America, the aerospace industry is vital. Natural Language Processing (NLP) is a technology developed in the early 1950s that analyzes language. Using artificial intelligence, it permits machine translation, speech recognition, thematic classification, and other modes of understanding and interpreting information. NLP technologies are integrated into various equipment and roles, including visual processing, systems monitoring and maintenance, risk assessment, design and prototyping, inspection, and reporting. These applications are applicable to the aerospace sector and have been successfully tested, developed, and marketed by many companies.

NLP is a suite of exploration technologies used to derive information, insights, and analyses from textual sources. A textual source can be any form of communication expressing thoughts, ideas, or concepts through letters and words. Simple textual sources are names and words, while complex ones are books, newspapers, and web pages. Exploration is a general term that means the extraction of information, insights, or knowledge from sources, while analysis is a more specific term that means summarizing basic characteristics, properties, or features.

Applications of NLP technology can be divided into three areas. "Mining" applications review textual sources gathered over time, summarizing, classifying, and categorizing them to allow human users to remain aware of the most important issues of concern. "Monitoring" applications continuously review and analyze a textual source, alerting when there is a change in its normal behavior or characteristics. "Process" applications automate natural language operations such as writing, translation, conversion to structured or numeric form, or extraction or visualization of specific information.

Exciting applications that have been successfully tested and developed are expressed in the terms just used for the three areas of concerns of NLP technology. NLP technologies are currently being integrated into various equipment and roles, such as visual processing, systems monitoring and maintenance, risk assessment, design and prototyping, inspection, and reporting. Some of these applications are in use in several aerospace manufacturing companies in the USA and Canada. Aerospace activities range from exploration and development to design, modeling analysis, fabrication, propulsion, monitoring, maintenance, documentation, and reporting.

3.1. Quality Control and Inspection

Several studies and projects have been carried out to utilize natural language processing (NLP) for quality control and inspection in aerospace manufacturing. Partly funded by NASA, Q-Scan by ITT - A ESI Group Company is a CSC designed to automate inspection, data management, and reporting tasks on thousands of Multi-Process/NDE Inspection job travelers. The process takes advantage of powerful intelligent data capture (IDC) and NLP algorithms to progressively extract, understand, integrate, and process unstructured textual quality inspection information. This allows rapid inspection setup for Multi-Process parts, with automatic generation of inspection traveler, PRT, reports, and related data items, and automatic processing of attached NDE data, including signature checking.

A follow-on implementation at a NASA (MDF) facility is underway with a major supplier, ARD. The prototype of Q-Scan has demonstrated the capability of rapidly (within a few hours) generating inspection travelers and associated reports that would normally consume months of labor. Other potential applications include automation of processing of other inspection job travelers types (doc type models) and platforms (Acrobat, EDS, newsprint, etc.). Internal projects have also been initiated to capture and make searchable other unstructured textual quality control evidence and inspection information, including quality and inspection related contract requirements (QICR), Material Review Board (MRB) dispositions and reports, etc.

3.2. Supply Chain Management

The supply chains that support economy-large production enterprises, such as the aerospace industry, are among the most complex, involving thousands of suppliers and a large number of materials and parts having many different characteristics [4]. The large number of participating firms and establishment locations suggest cost-effective long-distance transportation modes, which, combined with huge fixed costs, make the supply chain establishment and management process a very demanding optimization problem [5]. In an industry where products typically consist of thousands of parts and materials connecting hundreds of companies with complicated and cooperative contract agreements, the simultaneous management of supply chain logistics is a daunting implementation challenge. The development of state-of-the-art Natural Language Processing (NLP) methods has enabled the extraction of useful information from unfiltered natural language data sources such as news articles and social media. Current and past data from such sources can provide escalating awareness about the banking systems of commodity providing countries in a high temporal resolution.

NLP optimization models that will automate, optimize and streamline complex processes in aerospace manufacturing supply chains are proposed. Simulations of the models on sample supply networks illustrate their potential applicability to real-world supply chain operations of combining economic, environmental and economic indexes in an optimization framework to be taken into account when assessing supply chain establishment and enhancement strategies. Simulations of the models also provide possible new insights into the dynamics of complex supply chain operations of the aerospace industry.

4. Challenges and Limitations

Although NLP systems can bring many improvements to manufacturing processes, it is crucial to acknowledge the challenges and limitations. Addressing these challenges is key to realizing the benefits of this technology.

4.1 Data Privacy and Security Concerns

Implementing Natural Language Processing at all levels of American Aerospace manufacturing operations processes involves the processing and analysis of large amounts of data. Protecting proprietary information and complying with regulations is of critical importance. When organizations utilize cloud services to deploy NLP systems, they run the risk of exposing sensitive data to third-party providers. Consequently, ensuring data privacy and security is critical.

Various techniques can be employed to improve data privacy and security when deploying NLP models. For instance, federated learning allows models to be trained and updated on users' personal devices without transferring raw text data to centralized servers. Similarly, differential privacy perturbations can be added to the data in order to protect sensitive information while still creating useful models for downstream tasks. To explore these technologies, a clear investment strategy based on a comprehensive analysis of benefits and risks can help prioritize investments. A committee should supervise and execute this strategy, incorporating senior representatives from business functions, the IT office, and legal departments. This joint effort is essential in both regulatory compliance and risk management.

4.2 Integration with Existing Systems

Transitioning from mostly manual processes to advanced AI solutions requires organizational transformation. When automating lower-level functions, there may be concerns regarding employee resistance. In organizations relying on automatic processing, lower-level functions may already be performed by AI, allowing employees from other backgrounds to take on roles at a higher hierarchy level.

Integrating NLP systems with currently used software is another challenge. Often, a variety of different off-the-shelf or custom-made software solutions are in place, and the architecture of the corresponding IT system is unknown. Integrating new technologies across many types of hardware and software is a complicated challenge but must be undertaken if NLP solutions are to be used effectively. Solutions that do not integrate with moving parts will fail like a broken crane.

4.1. Data Privacy and Security Concerns

Even though natural language processing is efficient in many ways, several factors will increase the need for data security. As the technology is becoming more convenient, the more data-intensive the text corpora will become in order to enhance the revenues. This in itself could make it feasible for bad actors to exploit it. However, data security is integral to a project's enterprise security. Alongside the amount and breadth of documents, performances and the sophistication of NLP techniques have also contributed to growing pressures in the context of the model's data handling and security features. Such kinds of methods facilitate just the input and output models thereby the remaining part of the text they track. This default setting, however, can lead to data handlers with limited linguistic knowledge potentially exposing themselves to sensitive details.

Misclassification is done when language in itself poses a data secrecy threat. In contrast to traditional classification methods, text mining models zealously screens all words within the corpus thereby exposing the format by which sensitive data is displayed and thereby giving hackers knowledge on occurrences of such data, no matter how unclearly they are expressed. Companies may maintain detailed records of sensitive data in identifiable forms for the sake of having full paper records. For instance, an NLP device related to face recognition can lead to cameras identifying particular buildings. These structures may be used to perform nefarious deeds by shady individuals. However, by emulating company forms throughout their inherent language and revising the recovered textual details, NLP models might also cause potential harm. In the Alcoholics Anonymous Study, there is a "Working towards a Community Drinking" survey that contains recognizable individuals. They are asked drinking details, using very different wording.

4.2. Integration with Existing Systems

Challenges and Complexities of Integrating Natural Language Processing with Pre-existing Systems and Processes in the Aerospace Manufacturing Industry

Integrating Natural Language Processing (NLP) with pre-existing systems and processes poses challenges and complexities in the aerospace manufacturing industry. The aerospace manufacturing industry often implements different software solutions to manage vast amounts of documentation generated across diverse disciplines. Most of these design and analysis solutions, referred to as Computer Aided Engineering (CAE) or Computer Aided Design (CAD) tools, mainly focus on numerical computations [7] rather than addressing the need to manage textual information within highly structured design processes. This creates a rich multilingual textual environment leading to semantic fragmentation. As companies grow and develop, the need arises to improve the flow of textual information across disciplines. To do this, companies have begun considering the adoption of NLP technologies. However, these natural language technologies face implementation difficulties when integrated with pre-existing systems or processes. In most cases, the aerospace industry also has pre-existing systems and processes in place.

The aerospace design process and its textual information are first presented, followed by the presentation of NLP's capabilities and tools that can be utilized in this scenario. Then, common challenges and difficulties with adaptation and integration are discussed. Finally, the efforts made by two companies in seeking integrated solutions for application and adaptation of NLP technology are shown. Furthermore, the needs/niches of natural language technologies for the aerospace manufacturing industry are presented.

Aerospace Manufacturing Processes and the Generated Textual Data

Aerospace manufacturing companies operate multidisciplinary design teams that develop systems (aircraft, satellites, etc.) composed of several highly complex subsystems (mechanics, avionic, etc.). The design of these systems involves many interrelated design phases, such as requirements generation, system design and analysis, detailed design, and integration, verification and validation. The design processes are edified and implemented in a range of highly structured procedures. At the level of each design discipline, design processes comprise sets of sub-processes or concurrent work packages that are executed iteratively and inter-iteratively by cross-disciplined teams.

5. Case Studies

This case study focuses on one of the largest American Aerospace companies: Boeing. Boeing resides in the commercial airplane industry, one of the largest industries in the United States®. The commercial airplane business unit in Boeing manufactures airplanes whose parts are manufactured, assembled, and delivered worldwide. A distributed quality checking process is employed to check these manufactured parts to maintain certain quality standards. The scanned quality checking documents are unstructured textual data containing formatted reports and unformatted defect descriptions. To reduce the manual efforts, a Natural Language Processing (NLP) pipeline using Keyphrase Extraction and Clustering was developed to automate the categorization of defects mentioned in the checking documents.

There was significant improvement in the automatic checking process after the new NLP pipeline was implemented. More than 60% of the parts under inspection are automatically being checked for defects [8]. These defects generally had to be handled by manual inspection causing significant effort. Now with this new NLP pipeline on the checking documents, their categorization is automated which now requires a fraction of the effort compared to manual handling [9].

5.1. Boeing's Use of NLP for Quality Assurance

Boeing - the world's largest aerospace company and a leading manufacturer of commercial airplanes, as well as defense, space, and security systems - is also implementing the latest impact of natural language processing. With over 100 years of experience, it is no surprise that Boeing is implementing a state-of-the-business NLP capability. However, the astonishing thing is what it is using it for. With NLP technology and professional services, Boeing is solving an array of human capital challenges, including talent acquisition, taxation, and supply-demand. Building upon its AI leadership, Boeing is turning to NLP to fundamentally improve quality assurance, including parts inspection, the decollision system for wing assembly, and the elimination of human touch. Brains NLP tools process the entire lifecycle of data: from transcription, to tagging, to reinforcement learning with Boeing's proprietary machine learning models for natural language understanding and recommendations.

By transforming natural language data into market-winning user applications, Boeing has improved safety, quality inspection accuracy, and productivity. There is less risk and greater reliability in the broader detection of abnormal system response. Boeing has performed phenomenally well with NLP. Structures and systems employees have doubled their work while reducing their interaction cycle at wing assembly. Air France is now reliant upon Boeing's Proof of Concept. These NLP capabilities have on average saved Boeing up to 200 hours in time per petabyte when inspecting each wing side, and reduced the rate of unlocking secreted $400,000 annually. Atlantic partners negotiated an agreement to use NLP to further enable Boeing to understand how micro IIOW is being achieved. A leading aerospace who uses most of the high-value crown jewel large gear supplier wants to expand capacity but is retaining ownership of NLP really preventative.

United Technologies Corporation implemented NLP to process out-of-service medical parts, dismantled and stored in Rotable Inventory as part of the shared services function. Laundered parts are documented and used for repair processing at their repair facilities. Component and aggregate repair costs may decrease as a result.

6. Future Directions and Trends

Natural Language Processing (NLP), a crucial area in artificial intelligence (AI), focuses on the collaboration between humans and computers through natural language. It is an interdisciplinary field providing considerable opportunities for technological growth worldwide and is expected to grow by 21.5% during the period of 2022-2030. Recently, NLP has gained more attention with the advancements in neural networks, achieving state-of-the-art results on several NLP tasks. Along with deep learning technologies based on recurrent neural networks with attention mechanism, pre-trained language models such as ELMo, ULMFiT, BERT, and XLNet have advanced NLP modeling approaches significantly.

Despite rapid advancements in NLP, there are still several challenges to be addressed including its applicability to Low-Resource Natural Language (LRNL) understanding. The limited availability of training resources such as publicly available labeled data and sentimental dictionaries poses significant challenges in this regard. On the other hand, the over-sensitivity and controllability of NLP models are also critical issues to be considered. To simply assess the model quality on unseen examples, either an image or a text, humans are good at giving right answers most of the time. Several future directions have been identified amidst the challenges in NLP. There exist numerous future research directions for the community to explore.

One possibility lies in the area of machine learning. With more available data, algorithmic and data-oriented methods are expected to continue improving the robustness of NLP systems. Nevertheless, deep training on high-dimensional and long sequence structure input can easily incur increased computation, rendering the model difficult to analyze. Hence, there is a research opportunity to explore new types of model architectures, such as continuous-time recurrent neural networks and spiking neural networks, with potential implications for drastically improving efficiency and understandability of NLP systems. Another direction regards transferring knowledge from one task and data to another to mitigate the need for task-specific resources. Potential research can be dedicated to transfer learning techniques, including few- or zero-resource paradigms toward RL models.

6.1. Advancements in Machine Learning

[10]

Anticipated advancements in machine learning are relevant to the future of NLP in the aerospace manufacturing sector. Available innovations constantly add or remove technology and software used in aerospace design, analysis, and manufacturing. Considering this evolving landscape, two competing technologies are introduced: AWS and Initiative. Each positioned service gathering NLP advancements and tying them to a stream of innovation and technology building is equally important. Marketplace success depends on the contract's outcomes and commercialisation of technologies. Therefore, a community or ecosystem position is proposed for positive action instead of a zero-sum game of collecting innovations for each proprietary need [10].

On a global scale, machine learning and other technology advents used in a range of industries and streams of innovation might trickle down to the aerospace sector. With time, processes and solutions currently seen as commercially viable or best practices might even be used in smaller companies with more domain knowledge than needed outside the aerospace industry. If the aerospace industry does not act, ideas from its R&D field could be used commercially viable and take businesses away, resulting in operating losses. It is hoped developments will result in a pathway to understanding technology tracking, development connection, and desired outcomes on macro and micro levels.

7. Conclusion

Automation and tooling support technologies have contributed to the self-sufficiency of the aerospace and defense industry in the United States, empowering reliance on domestic suppliers of goods, materials, and services. Technologies like metrology, additive manufacturing, robotics, and digital information access scatter workforces across the nation. This proliferation leads to the need for National Work Control Technologies (NWCTs) that ensure aerospace and defense operations are productive, precise, and profitable. This study explored one approach to NWCT: Natural Language Processing (NLP) control technology. NLP systems guarantee operator performance agreement with training control policies through processing, evaluation, and time-stamped modification of operators' verbal outputs, enabling whole population control and organizations' structural optimization.

The application of an exploratory NLP system, Integrated Real-time Data Stock (IRDS), to the Airforce Installation and Mission Support Center (AFIMSC) was investigated, motivating a research program. IT systems at AFIMSC divert operators' verbal records in post-data format, lacking time stamps, relevance evaluation, and assessment of resultant operations. This limits organizations' awareness of workforce capabilities to on-paper indicators, impeding efforts to identify, eliminate, or migrate performance-inhibiting factors as waste. Controlled/NLP-compatible environments could be created by computationally transmuting post-data records to pre-data, pre-filtering, pre-evaluating, and augmenting them with time stamps. Adjustments departing from pre-approved development plans can be detected and flagged in operational code form.

Potential implications of NLP technologies for streamlined operations in the context of AFIMSC are presented. NLP systems could provide supervisors with quantitative indicators about operators' verbal outputs and performance, as well as recorded details of detected deviations and operative responses. No-priority avoidance of deviations would shape whole population performance and, in turn, a steep devolution of accumulated knowledge. Engaging undesirable operators in corrective verbal exchanges would regulate their verbal outputs and performance. NLP operators' profiles could depict the organizations' structural knowledge in terms of experience blanks or redundant verbalisms. Such profiles could elucidate workforce positioning weight on organizations' levels in terms of productivity versus intelligence. Performance-related frequency fluctuation maps could inform the operators' interference with decision-making data and associated waste types. Determined effort divergence indicators across operations would become available.

7.1. Summary of Findings

Modern aerospace manufacturing in the United States relies heavily on advanced complexity and adaptability, creating numerous challenges in operations, aerodynamics, engineering, assembly, and communications. Besides, as the amount of hard data scenarios increases, lines of communication within reports and documentation containing in-situ data scenarios fail to keep up. This results in the disruption of information streaming into computer-aided automation processes, hindering the ability of Artificial Intelligence (AI) techniques to produce solutions based on newly compiled information with meaning as it becomes available. There is thus the potential that Natural Language Processing (NLP) could be utilized to bridge the gap between the hard data scenarios and soft data communications, resulting in failures of streaming hard data becoming nonfeasible backlashes to responsiveness.

The core emphasis of this study was an analysis of how NLP could be adopted into the American aerospace and manufacturing industries to allow swift, tangible, and cohesive browsing capabilities of data resources, in a way that allows the smaller and more agile distributors of aerospace operations to take on deep-learning AI maximization and optimization techniques in the aggregate design of systems. A comprehension of the impact of NLP systems on streamlined operations regarding productivity enhancements, response capability, and maintainability was sought. Doing so would expose a prospective key player in ongoing entirety and entire domain problems, bringing about a need for experimentation before deploying modifications or provisions to operations, or purchasing technology that may not be entirely comprehensible or feasible. A summarization of findings from the investigation undertaken was presented.

The study established an understanding of NLP and motivations that are driving its reality. A runtime view of aerospace and manufacturing current and future operations was explored in-depth from an American perspective. Potential applications of NLP systems were deliberated along with a comprehension of their continued off-putting and limitations. Finally, a perspective on upcoming technological developments was provided, revealing conclusions in regard to the expansion of smart media and data indexed systems with the agency of NLP genre analysis and parse-formation techniques.

7.2. Implications for the Industry

In light of the growing competition, increased complexity, and higher customer expectations, American aerospace manufacturers face challenges in ensuring streamlined operations while improving productivity and providing better goods and services. However, this can be improved by integrating natural language processing (NLP) based systems to assist in achieving better operations. NLP, a critical component of artificial intelligence (AI), refers to the technology that can analyze, understand, and derive meaning from human language [11]. Although there are several barriers to the adoption of NLP, a USD 13 billion funding opportunity from the CHIPS and Science Act of 2022 can be used to develop better NLP technology for manufacturers and pave the way for smoother implementation with less burden.

The broader implications for the industry consist of the practical implications and consequences to be expected after integrating NLP into American aerospace manufacturing among several firms and the industry as a whole. Companies looking to enhance their productivity should be aware of this technology's industry-level impact and the various opportunities that can be generated from it.

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