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ANALYSIS OF TWEETS WITH #Covid19Vaccine SURROUNDING THE PERIOD OF COVID-19 VACCINE AVAILABILITY

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Abstract

This study analyzes public sentiment towards COVID-19 vaccines by focusing on Tweets containing the '#Covid19Vaccine' hashtag from October 2020 to April 2021. Out of the 108,025 Tweets collected, 103,210 were analyzed post-preprocessing. The study employs descriptive analysis, a Lexicon-based approach for Sentiment Analysis, and Latent Dirichlet Allocation (LDA) and K-Means clustering for Topic Modeling. The findings highlight significant public interest and media coverage of Pfizer and Moderna vaccines. The frequency of Tweets increasing after the release of the COVID-19 vaccine, compared to before, could be due to heightened public discourse and engagement on the vaccine's efficacy, distribution, and reception, as people shared information, experiences, and opinions on this significant development. The Sentiment Analysis showed a notable negative sentiment during the second week of October 2020. This stands out in contrast to other weeks, suggesting a specific event may have influenced the public mood. Topic Modeling results offer a comprehensive view of the public discourse, showcasing the challenges and successes encountered in the vaccination process. Consequently, this study recommends clear, evidence-based communication and proactive engagement by health authorities and pharmaceutical companies to effectively manage public sentiment and foster trust during health crises like COVID-19.

Keywords: *COVID-19, #Vaccince, Twitter, Sentiment Analysis, K-Means*

1. Introduction

The global health crisis triggered by the COVID-19 pandemic posed unprecedented challenges to healthcare infrastructure and significantly influenced the collective psyche worldwide. As various countries struggled to manage the surges of infection, developing and deploying a COVID-19 vaccine became a critical milestone (Graham, 2020). The release of the vaccine, a remarkable achievement in medical science, was met with a spectrum of public reactions, from enthusiastic acceptance to cautious skepticism (Shimabukuro, 2021). Social media platforms, particularly Twitter, transformed into hubs for diverse viewpoints, reflecting various attitudes towards vaccination (Murić & Ferrara, 2021; Tavoschi et al., 2020). This study explores these complex public sentiments, employing data science methodologies to unravel the changing perceptions about the COVID-19 vaccine.

Recent studies using social media, particularly Twitter, the most widely used platform for public discourse during the pandemic (Saraykar, 2021), have provided significant insights into societal sentiments and behaviors regarding COVID-19 vaccines. Alotaibi et al. (2023) utilized deep learning to analyze the causes of vaccine rejection based on opinions expressed on Twitter, providing a varied understanding of resistance to vaccination efforts. Wang et al. (2023) integrated a vast dataset of

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11 million Tweets with surveillance data across 180 countries to trace diverse and evolving sentiments towards vaccines, offering a global perspective on public opinion. Almars et al. (2022) delved into the emotional landscape of social media users, tapping into their opinions and feelings about the COVID-19 vaccine and highlighting the emotional undertones accompanying vaccine discussions. Also, Chen, Chen, & Pang (2022) compiled a multilingual dataset to capture vaccination attitudes on Twitter, reflecting a variety of linguistic communities, while Xu et al. (2022) conducted Sentiment Analysis and subject distillation from Twitter data, termed 'vaccine sensing,' to distill the essence of public opinion on the subject.

While substantial research has focused on understanding public sentiment toward COVID-19 vaccines using social media data, there remains a notable gap in the literature concerning the period before the vaccines' release. Studies by Alotaibi et al. (2023), Xu et al. (2022), and Almars et al. (2022) have analyzed Twitter data exclusively from the post-release period, missing a crucial phase where pre- release sentiments could have significantly influenced public perception and acceptance of vaccination campaigns. Furthermore, although other researchers such as Wang et al. (2023), Chang et al. (2022), and Chen, Chen & Pang (2022) have encompassed both pre- and post-vaccine release data, their approaches have not applied a focused data collection strategy akin to our study's use of the specific hashtag #Covid19Vaccine. The targeted use of this hashtag in data collection serves to refine the dataset, ensuring the extracted sentiments pertain directly to the vaccine itself, thereby reducing the noise from broader discussions that could potentially skew the Sentiment Analysis towards non-vaccine- related political or social issues. This is supported by the research of Dovgopol & Nohelty (2015), which indicates that hashtags in Twitter data play a crucial role in enhancing data relevance and minimizing noise, especially within hashtag recommendation systems, information retrieval, and content categorization. They highlighted the importance of hashtags in organizing the vast information space on Twitter. This precision filters out irrelevant discourse, providing a more accurate reflection of vaccine- centric public sentiment.

Additionally, this study introduces the use of the AFINN custom dictionary for Sentiment Analysis, a methodology not previously employed by the cited scholars. The AFINN dictionary provides a distinct lexical approach to sentiment scoring, which may capture variations in public opinion that other Sentiment Analysis tools overlook. Lastly, our study advances the analytical methodology by combining Latent Dirichlet Allocation (LDA) and K-Means clustering for Topic Modeling. This dual-method approach provides a more robust analysis by cross-verifying topics identified through both techniques. It ensures greater thematic clarity by selecting the best model that minimizes topic overlap, a feature not commonly addressed in existing literature. This methodological enhancement can potentially reveal more defined and discrete topics within public discourse, which can be pivotal for understanding the multifaceted nature of vaccine sentiment.

Hence, the primary aim of this study is to harness sophisticated data analysis methods to decode and interpret the public sentiment regarding COVID-19 vaccines as reflected on Twitter. The study seeks to categorize Tweets into positive, negative, or neutral sentiments, thereby mapping the general emotional tone of the vaccine-related discourse. It also aims to identify key themes and patterns within these Tweets, illuminating major concerns, misinformation, or skepticism among Twitter users about COVID-19 vaccines. This endeavor is crucial, as it can inform public health communications, policymaking, and community engagement strategies to enhance vaccine distribution and uptake efficiency. Our methodological approach stands out for its comprehensive scope and innovative techniques.

The paper is thoughtfully structured into six sections, guiding the reader through a coherent narrative of our research. It begins with an introductory overview and a comprehensive literature review that contextualizes our study within existing research and identifies critical gaps. The methodology section describes our data collection, pre-processing, and analytical techniques. In the 'Analysis and Results' section, we present our main findings, discussed in depth in the 'Discussion of Findings' section, situating our results within the larger context of vaccine-related sentiments. The study concludes with the 'Conclusion and Further Directions' section, discussing the implications, limitations, and potential future research directions in this critical area.

2. Methodology – Literature Review

The discourse on COVID-19 vaccination sentiments has dramatically benefited from diverse research methodologies, each contributing unique yet interconnected insights. During the pandemic, the intricate degrees of public sentiment were a focal point for researchers, who leveraged the extensive data available on digital platforms. This exploration was crucial in understanding the multifaceted public opinions during this global health crisis.

Almars et al. (2022) analyzed Tweets post-vaccine release to understand public emotion and opinion, finding predominantly positive sentiments. Their methodology hinged on emotion analysis using a deep learning model, which was notably accurate in classifying sentiments from around 50,000 Tweets. They found that many Tweets expressed positive feelings towards the COVID-19 vaccine. Their deep learning model, validated over a dataset of Twitter conversations, demonstrated high accuracy in sentiment classification, with up to 98% for the training set and 73% for the testing set. Also, Chang et al. (2022) investigated how the public views vaccines. They applied Sentiment Analysis and Topic Modeling, revealing an increase in concern concurrent with vaccine rollouts, yet the overall sentiment was positive, discussing vaccine efficacy, safety, and government policies.

Similarly, Chen, Chen, and Pang (2022) created a multilingual dataset from approximately 2.2 million Tweets from Western Europe. They used deep learning for sentiment classification. This dataset enables the development of data-driven models to understand public sentiments from social media, thus contributing to public health surveillance and informing future research. Wang et al. (2023) combined Sentiment Analysis of 11 million Tweets with health data across 180 countries using Sentiment Analysis. They found that sentiments became increasingly positive alongside a subsequent rise in vaccination uptake. The research also revealed different sentiment patterns across demographic groups. It emphasized integrating social media and public health data to understand population-level vaccination trends better.

Alotaibi, Alomary, and Mokni (2023) focused on vaccine rejection, sorting through over 200,000 Tweets. They used multi-class Sentiment Analysis with machine learning and deep learning models to classify people's opinions from Tweets about COVID-19 vaccines and identified five leading causes of vaccine rejection: lack of safety, side effects, production problems, fake news, misinformation, and cost. Their analysis found Decision Trees and Gated Recurrent Unit models to be most accurate for Sentiment Analysis, with LSTM models performing best in classifying Tweets according to rejection causes. Lastly, Xu et al. (2022) analyzed sentiments towards Chinese vaccines from about 5.3 million Tweets, identifying variances in opinion potentially influenced by pandemic statistics. They applied VADER and LDA for Sentiment Analysis and topic distillation, respectively, and found differences in sentiment towards Chinese vaccines compared to others, noting that daily cases and death counts could influence sentiment. They used topic analysis to identify significant areas of public concern, providing insights into vaccine trust and international public opinion.

Our research stands as a bridge in this academic landscape, offering a comprehensive analysis of over 100 thousand Tweets from October 2020 to April 2021, identifying the sentiment before and after the release of the vaccine. We employed Latent Dirichlet Allocation, K-Means Clustering, a custom AFINN sentiment dictionary, and innovative visualizations like Sunburst charts.

3. Literature Review

3.1 Data Collection Pre-processing

For the data collection phase, we harnessed the GetOldTweets3 API to capture Tweets related to COVID-19, specifically those tagged with '#Covid19Vaccine,' from October 1, 2020, to April 30, 2021. This initial retrieval yielded 108,025 Tweets. Our data cleaning involved removing retweets and duplicates, as well as standardizing the text by converting it to lowercase, and stripping punctuation and stop words. These measures refined our dataset to 103,210 Tweets, forming a robust foundation for in-depth Sentiment Analysis on COVID-19 vaccination discourse on Twitter.

3.2 Sentiment Analysis

Sentiment Analysis examines textual data to ascertain its emotional tone, such as positive, negative, or neutral. This field encompasses techniques ranging from machine learning, where algorithms learn to classify sentiment based on product reviews or social media posts (Aung & Myo, 2017), to lexicon-based strategies that utilize a predefined list of words with assigned sentiment values to gauge the tone. According to Zhang, Gan, and Jiang (2014), there are various methods within the lexicon-based strategy: the manual approach, which is labor-intensive; the dictionary-based method, which expands on a core set of known sentiment words by using resources like WordNet; and the corpus-based technique, which relies on a body of text to identify and understand sentiment expressions in context, though it may not be as comprehensive as the dictionary method. To capture public opinion, these tools are essential for describing through vast amounts of user-generated content, such as product feedback and social media commentary.

We utilized the AFINN Lexicon, a wordlist with over 2,400 terms; each assigned a sentiment score ranging from -5 to +5. This range effectively captures the intensity of sentiments expressed in language. We augmented the AFINN Lexicon with 35 new terms relevant to vaccine discourse, such as 'headache,' 'fever,' and 'affected,' adding them with negative scores due to their common negative connotations in vaccine discussions. Additionally, we scrutinized random Tweets to identify and incorporate terms not already present in the lexicon, ensuring our Sentiment Analysis was finely tuned to the vaccine conversation. AFINN is appreciated for its simplicity and ease of use, allowing quick sentiment scoring of texts without complex processing.

The AFINN Sentiment Analysis method offers a distinct advantage over machine learning (ML) and deep learning (DL) approaches, particularly in the context of its requirement for manual labeling. Unlike ML and DL methods, which necessitate the labor-intensive and time-consuming task of manually labeling a significant volume of Tweets to train the models effectively, AFINN operates on a lexicon-based approach. This technique leverages a predefined list of words, each assigned a sentiment score, to evaluate the overall sentiment of a text. This simplifies the process by eliminating the need for a vast corpus of labeled data and enhances the method's accessibility and efficiency in applications where rapid or resource-constrained Sentiment Analysis is necessary (Pang & Lee, 2008; Nielsen, 2011). So, we used AFINN method to calculate the sentiment scores based on the context of our problem. This has been utilized in the context of smart cities to understand people's concerns about daily life through social media analysis, involving statistical processes for sentiment recognition (Estévez-Ortiz, García-Jiménez, & Glösekötter, 2016).

3.2 Topic Modeling

Topic Modeling is a data science technique that helps uncover hidden patterns in a collection of texts (Likhitha, 2019). Imagine you have a massive pile of documents and want to sort out what main topics are being discussed without reading each one. That is what Topic Modeling does. It analyzes the words and phrases in the documents and groups them into topics. Each topic is a mix of terms that frequently appear together. For instance, in a set of news articles, Topic Modeling might find topics like "politics," "sports," or "economy" based on the clustering of related words. This way, it helps to quickly understand the main themes in an extensive text collection.

The first method employed for this study is Latent Dirichlet Allocation (LDA). LDA is a widely used technique in natural language processing (NLP) for uncovering latent topics from large volumes of text. Although LDA is not a technique specific only to Topic Modeling, it has been used widely for Topic Modeling with good outcomes in many research studies (Lee et al., 2022; Hu et al., 2023). Also, LDA's versatility allows it to be adapted for various other analytical tasks like information retrieval, document classification, and content recommendation (Hu et al., 2013; Leskovec et al., 2009).

Similarly, K-Means, a clustering algorithm used in unsupervised machine learning, can be applied in Topic Modeling by partitioning data into clusters based on feature similarity. However, K-Means can be adapted for a type of Topic Modeling where texts are represented as high-dimensional vectors. Each cluster can then be interpreted as a "topic," with texts in the same cluster being more similar in context (Rashid et al., 2020).

Our study explored Topic Modeling using Latent Dirichlet Allocation (LDA) and K-means clustering to sift through vast Twitter data. After extensive iterations, we identified seven as the optimal number of unique topics within the Tweets. The findings suggested that K-Means Clustering provided more apparent separation between topics than LDA, with less overlap in Tweets categorized under different topics. We manually named the topics to make sense of these clusters by reviewing each group's top words and Tweets. This method allowed us to identify distinct conversation themes and provided structured insights from the unstructured Twitter data.

4. Analysis and Results

4.1 Descriptive Analysis

We commenced our assessment with a descriptive analysis of the collected data. Figures 1 and 2 present the most common top 20 hashtags and top 20 mentioned usernames, exclusively within the context of Tweets related to the COVID-19 vaccine that included the '#Covid19Vaccine' hashtag.

Figure 1 provides an analysis of Tweets frequencies. Starting in December 2020, there has been a noticeable surge in Tweet volume, which aligns with the release of the first COVID-19 vaccines. In this analysis, the Pfizer vaccine dominates, featuring 2,437 Tweets, while the Moderna vaccine follows, with 1,915 Tweets. This pattern reflects the early approval and widespread discussion of Pfizer and Moderna vaccines on Twitter. The high frequency of these Tweets can be attributed to various factors such as public interest, media coverage, and the pivotal role these vaccines played in the initial phase of the COVID-19 vaccine rollout. Also, it shows a greater public interest in specific vaccine brands rather than the regulatory processes of the FDA or the stances of US Presidents on vaccines.

Figure 2 analyzes the frequency of mentions for the top 20 users. Here, @pfizer emerges as the most mentioned username with 1,204 Tweets, highlighting the pharmaceutical company's centrality in vaccine-related discussions on Twitter. The high frequency of @pfizer mentions reflects the public's attention to and engagement with the company, given its leading role in developing one of the first COVID-19 vaccines. Again, diverse groups encompassed various entities, ranging from vaccine manufacturers to well-known personalities, media outlets, U.S. Presidents, organizations, and political figures, reflecting a broad spectrum of influential voices in the vaccine dialogue.

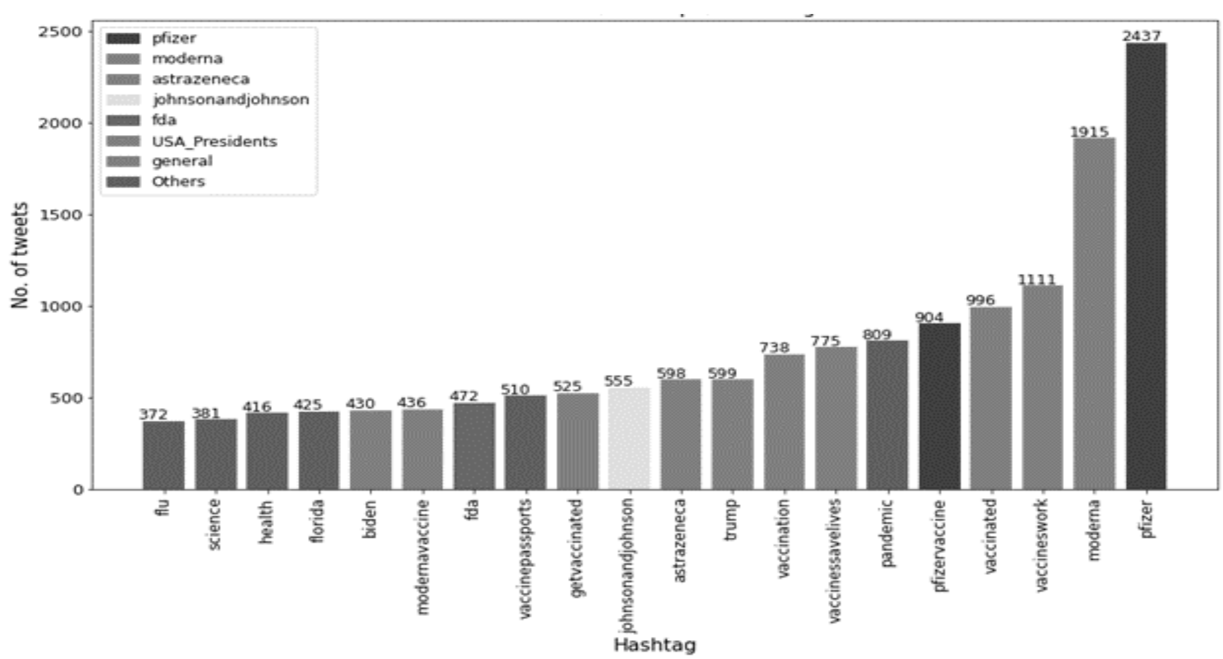


Figure 1: Frequency of Top 20 Hashtags

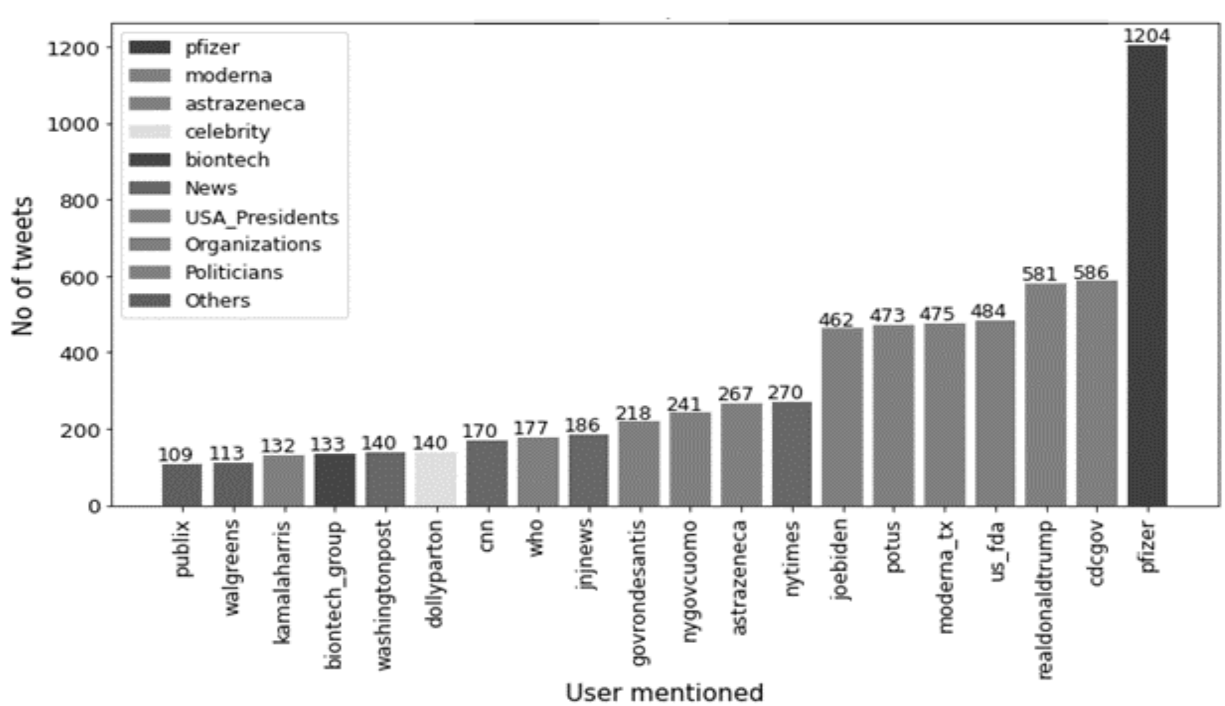


Figure 2: Frequency of Top 20 User Mentions

4.2 Sentiment Analysis

Figure 3 utilizes a bar chart to depict the mean sentiment of Tweets over time. In the graph, bars extending above the 0.0 mean sentiment score indicate positive sentiment, whereas bars dropping below this threshold represent negative sentiment. The absence of a bar depicts periods with a neutral sentiment. This method of visualization enables an intuitive understanding of sentiment changes over time. To add further context, a vertical line has been integrated into the visualization to mark the week when the vaccine became available. This distinction is essential for associating key events with sentiment trends. Furthermore, a line graph overlaying the bar chart shows the volume of weekly Tweets, providing a comprehensive view of the intensity of online discourse about vaccines during the studied timeframe.

We evaluated the Sentiment Analysis and found that the sentiment graph presents a distinctive pattern. A mix of positive and negative sentiments is marked by the dashed line before the vaccine release. The sentiments fluctuate weekly but generally show more positive reactions. There is a negative sentiment during the second week of October 2020. This stands out in contrast to other weeks, suggesting a specific event may have influenced the public mood. The negative sentiment could be linked to the announcement by former President Donald Trump that he and the First Lady, Melania Trump, tested positive for COVID-19, which could have caused widespread uncertainty and concern.

After the vaccine became available, the positive sentiment spiked and followed a downward trend but remained higher overall than the negative sentiment. The chart suggests that the vaccine release likely boosted people's positive feelings, as indicated by the positive bars getting taller around that time. The high volume of Tweets, shown by the line graph, right after the vaccine release suggests a lot of discussions or reactions during that period. The reasons for these sentimental changes could range from relief and hope brought by the vaccine's availability to varying responses to the vaccine's effectiveness or side effects as more information became public.

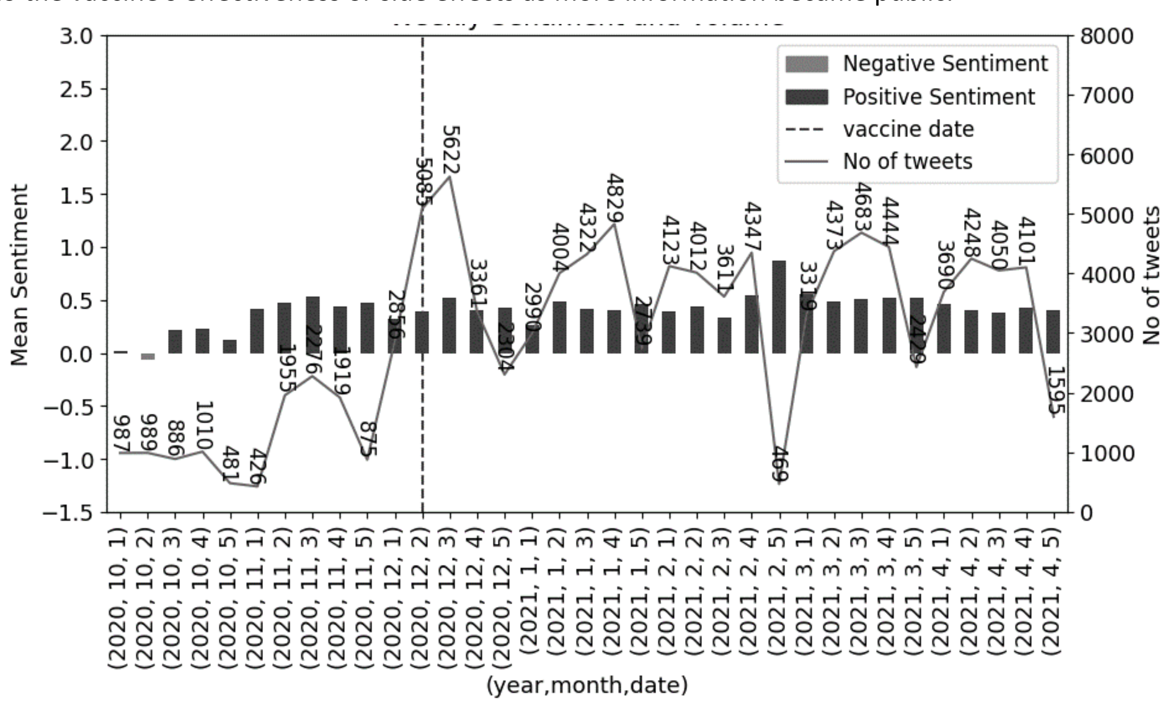


Figure 3: Week-Wise Average Sentiment and Volume of Tweets

4.3 Topic Modeling

After numerous iterations with both K-Means and LDA methods, we discovered that K-Means, with seven distinct topics, outperformed LDA in segregating the Tweets by topic. We experimented with topic ranges from 2 to 15 and scrutinized their outcomes. We observed that there was a blend of multiple topics within each category for fewer than seven topics. Conversely, we encountered redundancy for more than seven topics, with identical topics recurring and an overlap of Tweets from previously identified topics. For instance, Topic 2 predominantly concerns vaccine safety. However, when the number of topics exceeds seven, we notice some Tweets from this topic spill over into another, creating a composite of already identified topics. Consequently, the K-Means method achieved the clearest segmentation with seven topics.

The top ten words are determined based on the cluster centers, with each word's significance within the cluster gauged by its proximity to the centroid. By sorting these centroids and selecting the foremost words, the function pinpoints those that most accurately represent the content of each cluster. Utilizing these keywords, we can decipher the central themes or subjects within each cluster produced by the K- means algorithm.

Table 1: Topic Modeling

Word	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7
	Pharmacy Sabotage	Vaccine Safety	AstraZeneca Updates	Vaccine Logistics	Vaccine Advocacy	Pfizer Updates	Vaccine Appointments
Word 1	pharmacist	force	AstraZeneca	distribution	community	Pfizer	appointment
Word 2	ruin	people	update	plan	trusted	dose	county
Word 3	suspected	unsafe	oxford	state	join	Moderna	schedule
Word 4	doses	not safe	trial	challenge	access	today	today
Word 5	vaccination	shot	effective	health	center	BioNTech	make
Word 6	deliberately	dose	data	Pfizer	member	dose Pfizer	open
Word 7	news	health	news	administration	clinic	second dose	site
Word 8	arrested	eligible	latest	trump	hesitancy	Pfizer BioNTech	eligible
Word 9	health	black	efficacy	effort	protect	received	week
Word 10	state	taking	report	Biden	health	shot	dose

Table 1 summarizes the essence of these topics, with each column representing a cluster of conversation and the words listed under each topic heading reflecting the core subject matter of the Tweets within that cluster:

Topic 1 - Pharmacist Sabotage: depicts a situation where a pharmacist is accused of intentionally compromising the integrity of COVID-19 vaccine doses. The key elements indicating this theme are words such as "pharmacist," "ruin," "suspected," "deliberately," and "arrested." These Tweets likely discuss the incident, public reactions, and the potential impact on public health efforts. The topic encompasses the criminal act of Sabotage, the healthcare context involving vaccines, and the resulting legal and community response to such an event.

Topic 2—Vaccine Safety depicts the frustration and complexity of emotions surrounding the vaccine, as seen in the Tweets, where some people are hesitant, others are critical, and some advocate for or against the vaccine.

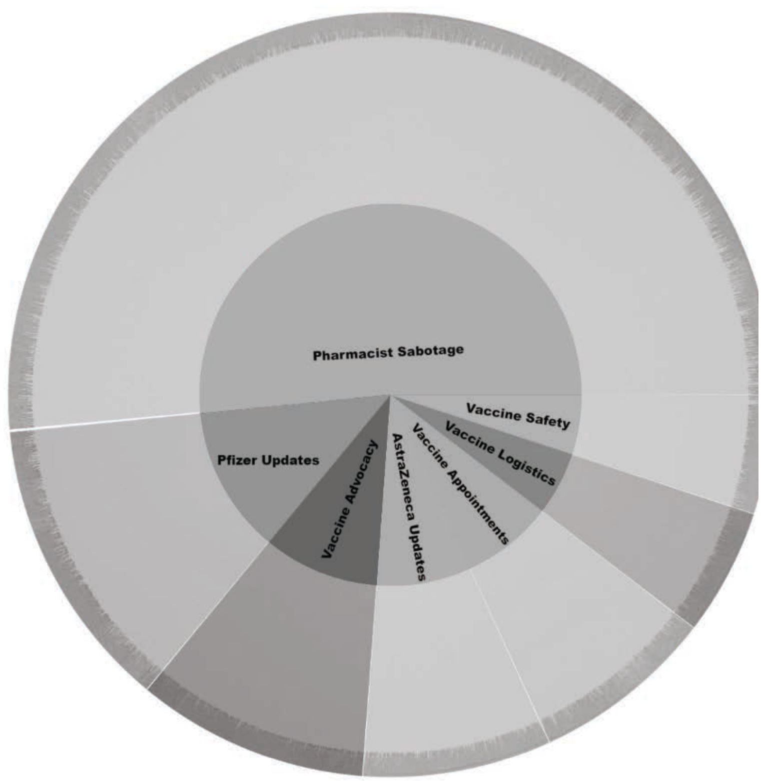
Topic 3—AstraZeneca Updates captures the international aspect of vaccine distribution and concerns, the evolving nature of the news and updates about the vaccine, and various angles, from efficacy and safety to ethical and economic considerations.

Topic 4—Vaccine Logistics captures the intricate dynamics of delivering vaccines in a pandemic. It reflects the logistical challenges, technological solutions, and mixed public sentiment, ranging from frustration over inefficiencies to optimism about technological interventions. This topic represents a cross-section of society's struggle and collective endeavor to navigate the complexities of a global health crisis.

Topic 5—Vaccine Advocacy encapsulates the essence of grassroots efforts and the pivotal role of trusted voices in overcoming vaccine hesitancy. It highlights diverse communities' outreach and educational initiatives to boost COVID-19 vaccine acceptance and access. This topic reflects collective action and localized strategies to protect health and foster inclusivity in public health responses.

Topic 6 - Pfizer Updates presents public reactions and perspectives on receiving the Pfizer COVID-19 vaccine, shared via social media posts. It reflects a blend of personal milestone announcements and gratitude towards healthcare providers. The conversation also touches on the scientific achievement of the vaccine’s development and its significance in combating the pandemic.

Topic 7 - Vaccine appointment examines individuals' varied experiences scheduling COVID-19 vaccine appointments. Posts demonstrate success and frustration, with some celebrating their scheduled appointments while others struggle to navigate the appointment systems. Challenges such as vaccine shortages, website issues, and the digital divide are highlighted, alongside the urgency many feel to secure a vaccine for themselves or their vulnerable family members. The content reflects the logistical complexities of massive vaccine rollouts and the emotional highs and lows of the public trying to access them.



5. Discussion of Findings

Amid the COVID-19 pandemic, understanding public sentiment toward vaccines has become crucial to managing the global health crisis. This study sheds light on these sentiments by analyzing over 100,000 Tweets with '#Covid19Vaccine,' capturing a picture of public opinion during a pivotal time in the vaccine rollout using descriptive analysis, Sentiment Analysis, and Topic Modeling. The study observed a notable increase in Tweet volume beginning in December 2020, coinciding with the introduction of the first COVID-19 vaccines. This surge suggests an escalation in public interest and engagement in vaccine discussions, particularly at crucial points in their availability. This finding resonates with the research of Almars et al. (2022), who also reported an uptick in social media activity following significant vaccine-related events.

Pfizer and Moderna emerged as predominant topics in the dataset, indicating a public focus on these specific vaccines, likely influenced by their early approval and extensive media coverage. This pattern aligns with the observations made by Chang et al. (2022), who noted similar trends in their analyses of vaccine-related discussions. Also, @pfizer was frequently mentioned, highlighting the pharmaceutical company's central role in public vaccine discussions. This might reflect the public's trust or scrutiny of the company. This finding is consistent with Chen, Chen, and Pang (2022), who emphasized the significance of pharmaceutical companies in vaccine discourse.

Similarly, a distinct sentiment pattern was observed: Before the vaccine release, the sentiments fluctuated weekly but generally showed more positive reactions. After the vaccine became available, the positive sentiment spiked and followed a downward trend but remained higher overall than the negative sentiment. The chart suggests that the vaccine release likely boosted people's positive feelings. The high volume of Tweets right after the vaccine release indicates many discussions or reactions during that period. The reasons for these sentimental changes could range from relief and hope brought by the vaccine's availability to varying responses to the vaccine's effectiveness or side effects as more information became public.

The study identified seven distinct topics, including Pharmacist Sabotage and Vaccine Safety. This emphasizes the diverse aspects of vaccine discourse, encompassing concerns, logistical challenges, and advocacy efforts. Similar thematic diversity was found in the analyses by Chang et al. (2022) and Xu et al. (2022), reflecting the multifaceted nature of discussions around vaccines. The use of Sunburst charts to illustrate the prevalence of topics and the relevance of Tweets within the dataset demonstrates the utility of innovative visualizations in understanding complex data sets. The analysis revealed that 'Pharmacist Sabotage' emerged as the leading topic in terms of discussion volume, indicating a significant level of public concern or interest in the integrity and safety of vaccine distribution. This was closely followed by topics such as 'Pfizer Updates,' 'Vaccine Advocacy,' 'AstraZeneca Updates,' 'Vaccine Appointments,' 'Vaccine Logistics,' and 'Vaccine Safety.' The size and placement of these topics within the Sunburst chart reflect their frequency in the dataset and highlight their importance in the public's perception.

The implications of the Topic Modeling and Sunburst chart analysis of the '#Covid19Vaccine' are significant for public health communication and policy. The prominence of topics like 'Pharmacist Sabotage' underscores the critical need to maintain and enhance public trust in vaccine distribution's safety and integrity. The focus on pharmaceutical companies such as Pfizer and AstraZeneca highlight their influential role in shaping public opinion, underscoring the necessity for transparent and proactive communication about vaccine developments. The substantial discussion around vaccine advocacy and appointments emphasizes the importance of accessibility and the effectiveness of public health campaigns. Furthermore, public awareness of logistical challenges calls for efficient management and communication regarding vaccine distribution. These insights are crucial for tailoring communication strategies and operational approaches to align with public sentiment, thereby enhancing public confidence and the effectiveness of the vaccine rollout.

6. Conclusion and Further Directions

Analyzing the '#Covid19Vaccine' dataset provides several critical conclusions about public sentiment toward COVID-19 vaccines on Twitter. First, the significant surge in Tweets volume starting in December 2020 indicates a heightened public engagement coinciding with the release of the first COVID-19 vaccine. This surge is mainly focused on the Pfizer and Moderna vaccines, as seen in the predominance of the

Pfizer and Moderna. This finding suggests that public attention was strongly oriented towards these vaccines, reflecting their early approval and widespread discussion in the media. Second, the frequent mentions of @pfizer point to a substantial public interest in and engagement with the pharmaceutical company's role in vaccine development. This suggests that the actions and communications of pharmaceutical companies are under intense public scrutiny and have a significant impact on public opinion regarding vaccines.

Third, the Sentiment Analysis showed a notable negative sentiment during the second week of October 2020. This stands out in contrast to other weeks, suggesting a specific event may have influenced the public mood. The negative sentiment could be linked to the announcement by former President Donald Trump that he and the First Lady, Melania Trump, tested positive for COVID-19, which could have caused widespread uncertainty and concern. The frequency of Tweets increasing after the release of the COVID-19 vaccine, compared to before, could be due to heightened public discourse and engagement on the vaccine's efficacy, distribution, and reception, as people shared information, experiences, and opinions on this significant development. This trend highlights the critical role of timely and transparent communication in shaping public sentiment. It underscores the need for ongoing engagement to maintain trust in public health initiatives, especially in vaccine distribution and adoption. Lastly, the topic identified encompasses various aspects such as public trust, logistical challenges, advocacy efforts, and personal experiences related to vaccine appointments, and the diversity of these topics reflects the multifaceted nature of public discourse surrounding the COVID-19 vaccines, highlighting the challenges and successes in the vaccination process.

The findings from this study provide valuable insights for health authorities, governments, and stakeholders in managing public sentiment during similar health crises in the future. The observed surge in social media engagement and shifting sentiments underscore the need for clear, evidence-based communication about vaccine efficacy and safety, particularly in the early stages of a vaccine rollout. The significant focus on pharmaceutical companies like Pfizer and Moderna highlights the importance of transparent communication from these entities. By addressing specific concerns related to vaccine safety, logistics, and appointments, authorities can mitigate skepticism and build public trust. Additionally, continuous social media monitoring can help quickly identify and respond to emerging concerns or misinformation. Collaborative efforts in vaccine advocacy and community engagement, tailored to the evolving stages of a health crisis, are crucial for fostering informed public discussions and enhancing vaccine uptake. These strategies are essential for effective crisis management and public health communication in future pandemic responses or similar situations.

For future research, leveraging Tweet data could offer a broader understanding of various conversations surrounding vaccines, including political discourse. Beyond analyzing political discourse, future studies could also explore the relationship between vaccine sentiment and real-world events using Tweet data. For instance, researchers could investigate how vaccine sentiment correlates with COVID- 19 infection rates, policy changes, or significant news announcements. Another avenue could be to examine the impact of influential users on Twitter, such as celebrities or public health officials, on public sentiment about vaccines. Additionally, comparing geographic variations in sentiment could offer insights into cultural or regional differences in the reception of the vaccine discourse. These approaches could provide a comprehensive picture of the factors influencing public opinion on vaccines.

7. Disclaimer Statements

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Conflict of Interest: None

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AI-DRIVEN PROJECT MANAGEMENT: CHALLENGES & OPPORTUNITIES

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Abstract

Project management (PM) has undergone significant transformation with the advancement of artificial intelligence (AI), which has introduced new capabilities for managing complex projects and streamlining processes. This paper aimed to explore the evolving role of AI in PM, highlighting key opportunities and obstacles for effective adoption. This paper addressed the successful integration of AI into PM by examining real scenarios that have occurred in various companies.

Keywords: *Artificial Intelligence (AI), Project Management (PM), Machine Learning (ML), Risk Management, Process Optimization*

1. Introduction

In an era of increasing project complexity and rapid technological advancement, the integration of artificial intelligence (AI) into project management has emerged as a transformative force. Traditional project management relies heavily on human expertise, intuition, and historical knowledge to drive decision-making, often leading to inefficiencies, biases, and limitations in scalability. AI-powered tools offer a paradigm shift by introducing automation, predictive analytics, and data-driven decision-making, enabling project managers to optimize workflows, mitigate risks, and enhance overall efficiency. As organizations across industries adopt AI-driven solutions, project management is evolving into a more agile, intelligent, and data-driven discipline.

Savio & Ali (2023), stated that project management is a cornerstone of organizational success, focusing on achieving objectives within defined constraints of time, budget, and scope. Dima (2020) argued that as projects grow in complexity, traditional methodologies, including the Waterfall and Agile frameworks, face challenges such as inefficiencies, human biases, and data silos. Hashfi & Raharjo, (2023) highlighted that the application of AI offers solutions to these challenges by automating repetitive tasks, improving forecasting, and optimizing resource allocation. Savio and Ali (2023) further explained that AI technologies analyze historical project data to identify trends, assess risks, and provide actionable insights, which enhances decision-making and mitigates common project management challenges such as scope creep, resource allocation issues, budget overruns, and scheduling conflicts. By leveraging machine learning algorithms and predictive analytics, AI helps project managers anticipate potential roadblock, optimize workflows, and improve overall project success rates. For instance, Hashfi & Raharjo (2023) emphasized that AI-driven tools like natural language processing streamline communication, while predictive analytics improve risk assessment and timeline accuracy. As industries adopt AI to address gaps in traditional project management,

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understanding its implications becomes critical to leveraging its potential effectively.

Conventional methods for project management place a significant cognitive and operational burden on project managers, requiring them to make critical decisions based on personal experience, professional training, and historical knowledge. While this experiential approach provides valuable insights, it also introduces inherent subjectivity, increasing the risk of cognitive biases, both positive and negative, that can influence decision-making. These biases may affect key aspects of project execution, including risk assessment, resource allocation, and stakeholder communication, potentially leading to inefficiencies or suboptimal outcomes. As project complexity grows, reliance on individual judgment alone becomes increasingly insufficient, underscoring the need for data-driven, AI-enhanced decision-making frameworks that minimize bias and enhance project performance.

Additionally, the prospect of AI being applied outside of traditional methods cannot be ignored. Agile Project Management (APM), which relies on a successive cycle of iterations (commonly referred to as “sprints”), is commonly applied within the field of software development and engineering. It is often characterized by, and thus favored because of, the ability to relatively rapidly produce deliverables and adapt to customer needs and specifications.

This paper explores the integration of artificial intelligence (AI) in project management, analyzing both its challenges and opportunities. It examines how AI-driven tools enhance decision-making, automate repetitive tasks, optimize resource allocation, and improve collaboration, ultimately increasing project efficiency and success rates. Additionally, the paper addresses potential limitations, including implementation challenges, ethical concerns, and the evolving role of project managers in an AI-driven landscape. By evaluating real-world applications and industry case studies, this study provides insights into how AI is reshaping the future of project management.

2. Literature Review

Savio & Ali (2023) defined Artificial Intelligence (AI) as the simulation of human intelligence by machines that encompasses technologies like machine learning, natural language processing (NLP), and robotic process automation (RPA). Since its inception in the 1950s, AI has evolved from theoretical applications to practical tools that reshape industries, including project management. Hashfi & Raharjo, (2023) noted that in project management, AI offers capabilities such as automating scheduling, optimizing resource allocation, and enabling predictive insights that align with project goals. Dam et al. (2018) explained that these technologies are becoming integral to managing the increasing complexities of modern projects, reducing inefficiencies, and ensuring timely and cost-effective project completion. However, implementing AI also raises challenges, including data quality issues, ethical concerns, and the need for workforce upskilling. Understanding these dynamics is essential for organizations aiming to adopt AI-driven project management practices successfully.

Odejide & Edunjobi (2024) described two distinctive artificial intelligence methodologies that are relevant to project management. One example, Machine Learning (ML), is particularly useful in the context of a well-documented history due to the ability to thoroughly analyze historical data and identify features, such as patterns and trends, that may be difficult for humans to identify. Theoretically, by allowing for easy analysis of a vast amount of historical information, a project manager would be able to use that information to make decisions which would minimize disruption. Another possibility, Deep Learning (DL), has applications in less structured contexts. The authors further explain DL, named for the attempt at emulating the structure and function of the human brain, is capable of reasoning to an extent, which would enable it to ascertain possible project trajectories using the aforementioned historical data and trends. Ideally, DL-generated courses of actions would have to be approved by a human being to maintain oversight and assure a degree of accountability in the event of an unfavorable outcome.

In recent times, AI technology has seen a considerable amount of attention, both positive and negative. Amidst the concerns about data privacy and accuracy, there is a distinctive degree of potential for improvements to numerous processes offered by this technology. It is due to this split nature and the potential impact across numerous industries that it can be considered a particularly disruptive new technology. Odejide & Edunjobi (2024) suggested that there is a strong possibility for technology to benefit individuals in project management by streamlining the process of conducting projects across both large and small scales. Given that many of the issues facing project management in complex settings stem from human issues, such as difficulties in decision making and risk management, the added automation would theoretically lead to a reduction in the impact of human error. Additionally, it can be inferred that by increasing the availability of statistical information, a project manager would be able to effectively limit the presence of bias in the decision-making process.

Returning to the concept of agile project management, there are several challenges associated with this general method. As explored by Dam et al. (2018), many of them are typical of project management; poor communication, allocation of resources, and priority issues can plague a project regardless of approach. As a result, a wide range of software tools have been developed to assist teams working on APM teams, though they often come with glaring limitations. These limitations include a lack of proactive analytical tools. Thus, by assisting with the pervasive and complex topic of analytics, data analysis is made more readily available to the project team and manager, which would hypothetically facilitate communication and allow for more easy assignments of resources and priorities.

Understanding the intersection of AI and project management is crucial, as it presents a multifaceted landscape of challenges and opportunities. While AI can enhance decision-making accuracy, reduce human error, and improve time management, it also introduces concerns related to the need for professional oversight, data privacy, algorithmic transparency, and potential displacement of human roles. Furthermore, the successful integration of AI into project management practices necessitates overcoming technical and cultural barriers within organizations. Thus, a comprehensive examination of both the potential benefits and the inherent challenges of AI in project management is essential for harnessing its full potential. This paper aims to explore the evolving role of AI in project management, highlighting key opportunities while addressing the obstacles that must be navigated to ensure effective adoption.

3. Opportunities for AI in Project Management

The integration of AI in project management presents numerous opportunities to enhance efficiency, accuracy, and decision-making. By automating repetitive tasks, optimizing resource allocation, and improving collaboration, AI enables project managers to focus on strategic planning and innovation. AI-driven tools also support agile methodologies, enhance risk assessment, and reduce human error, leading to more predictable and successful project outcomes. This section explores key opportunities that AI offers, demonstrating how its adoption can transform project management practices across industries.

3.1 Enhancing Decision-Making

Hashfi & Raharjo (2023) emphasized AI's potential to enhance project management processes is immense. One of its most notable contributions is its ability to improve decision-making through advanced data analysis. AI systems can process vast datasets, identifying patterns and providing actionable insights that enable more accurate cost forecasting, resource allocation, and scheduling. Additionally, Pan & Zhang (2021) asserted that tools such as predictive analytics and machine learning offer superior capabilities for planning and monitoring, allowing project managers to anticipate risks and implement corrective measures proactively. These advancements not only streamline project workflows but also enable significant time and cost savings.

3.2 Process Optimization

Jiang (2021) stated that process optimization is another critical area where AI has demonstrated its value. He continues by saying technologies such as Building Information Modeling (BIM), the Internet of Things (IoT), and machine learning algorithms support real-time monitoring, allowing project managers to make data-driven decisions and adapt to changing circumstances dynamically. For instance, Karatas & Budak (2024) discussed that AI-powered systems can optimize resource utilization and predict labor productivity, ensuring that projects adhere to timelines and budgets. Furthermore, AI's automation capabilities reduce human error and free up resources for strategic tasks, enhancing overall project efficiency.

3.3 Automation of Repetitive Tasks

AI-driven automation streamlines repetitive tasks such as scheduling, data entry, and progress tracking, allowing project managers to focus on strategic decision-making. According to Moss (2025), Willmott Dixon, for example, uses AI-driven automation to minimize errors and optimize resource allocation, demonstrating how AI can improve overall project efficiency. Similarly, Garza (2018) reported that Bechtel applies AI in construction sequencing to enhance scheduling accuracy and reduce site density issues, highlighting the value of automation in complex project environments.

3.4 Improved Resource Allocation

Hashfi & Raharjo (2023) stated that AI enhances resource allocation by analyzing historical data and predicting future needs, enabling more accurate and dynamic resource management. AI-powered systems provide actionable insights that help project managers adjust workloads and distribute resources more effectively, leading to improved productivity and reduced waste. Moss (2025) highlighted Willmott Dixon's integration of AI for workflow optimization as a strong example of how AI can enhance resource utilization.

3.5 Support For Agile Projects

Agile Project Management (APM) benefits significantly from AI's predictive capabilities and real-time monitoring. Dam et al. (2018) explained that AI supports sprint planning and progress tracking, improving responsiveness to changing project requirements. AI-driven tools analyze team performance and suggest adjustments to enhance delivery speed and quality. This dynamic feedback loop strengthens the agility of project teams and fosters continuous improvement.

3.6 Improved Communication and Collaboration

AI facilitates improved communication and collaboration through natural language processing (NLP) and automated reporting. A recent study by Vergara et al. (2025) founded that AI-driven platforms generate real-time updates and insights, ensuring that all stakeholders are aligned and informed. This enhanced transparency promotes better coordination and faster resolution of issues, contributing to smoother project execution.

3.7 Digital Assistant to Project Manager

Another considerable application for AI tools is the potential to streamline the individual workload of a project manager. As stated by Mikhaylov (2023), artificial intelligence can be a tool to reduce the quantity of routine work expected of a project manager, which would enable them to focus on more critical tasks such as collaboration or complex management tasks. In essence, the adoption of artificial intelligence programs can ultimately streamline the process of management and aid in overall efficiency, enabling managers of complex projects to devote more time and effort to more important tasks.

4. Challenges of AI in Project Management

4.1 Data-Related Issues

While AI offers significant advantages in project management, its implementation comes with notable challenges. Issues such as data privacy concerns, integration complexities, and the need for specialized expertise can hinder adoption. Additionally, AI-driven decision-making may introduce ethical dilemmas, reduce human oversight, and create resistance among project teams accustomed to traditional workflows. Ensuring transparency, accuracy, and alignment with organizational goals remains critical for successful AI integration. This section explores the key challenges organizations face when incorporating AI into project management and discusses potential strategies to address them.

Hashfi & Raharjo (2023) noted that despite these advantages, integrating AI into project management is not without challenges. Data-related issues remain a primary concern. AI systems rely heavily on accurate and complete datasets to function effectively. However, inconsistencies in data quality and difficulties in integrating information from multiple sources often undermine the reliability of AI outputs. Additionally, Victor (2023) highlighted the high costs associated with implementing AI technologies, including hardware, software, and training, can be prohibitive for many organizations. Ranesh et al., (2022) further emphasized that these technical barriers are further compounded by interoperability challenges, which arise when attempting to integrate AI systems with existing project management tools.

Another significant concern is the legal risk associated with AI-driven project management, particularly in terms of liability and data privacy. As AI takes on more decision-making responsibilities, determining accountability in cases of errors or project failures becomes increasingly complex. Organizations may face legal disputes over whether responsibility lies with the AI provider, project managers, or developers who configured the system. Furthermore, AI systems processing personal data of project team members introduce risks of unauthorized access or breaches, potentially violating data protection regulations. If sensitive information is mishandled, companies may be subject to legal penalties, reputational damage, and loss of stakeholder trust.

4.2 Skilled Workforce Concerns

However, its negative effects also give rise to several challenges, particularly concerning workforce displacement and declining critical thinking skills. Eng & Liu (2024) pointed out that as intelligent software and automated machinery continue to replace traditional manual labor, industries experience a reduction in demand for human workers, leading to increased unemployment and economic instability. Furthermore, the growing reliance on AI-driven tools may contribute to a decline in problem-solving abilities, as individuals become accustomed to automation handling complex tasks. This overdependence on intelligent systems can discourage continuous learning and innovation, particularly among younger generations seeking rapid success through technological shortcuts.

4.3 Resistance to Change

Alshaikhi & Khayyat (2021) mentioned that resistance to change is another significant hurdle. Human factors, such as fear of job displacement and reluctance to adopt new technologies, can impede the widespread acceptance of AI in project management. Project managers often struggle to adapt to AI-enabled systems, requiring extensive training and a cultural shift within organizations to overcome these barriers. Furthermore, ethical and legal concerns, including data privacy, accountability, and transparency, present additional challenges that organizations must address to ensure responsible AI adoption.

4.4 Managing Uncertainty and Variability

Alshaikhi & Khayyat (2021) mentioned that uncertainty and variability in project environments also pose difficulties for AI implementation. Projects often face unique challenges that AI systems, designed on predefined algorithms, may not adequately account for. This limitation necessitates the development of more adaptable and context-sensitive AI tools. Moreover, the complexity of aligning AI tools with specific project requirements underscores the need for skilled personnel capable of navigating these intricacies.

4.5 Ethical Concerns in Algorithmic Decision-Making

A noteworthy constraint placed upon the implementation of AI within project management frameworks is the moral and ethical implications of decisions made by a program. For an algorithm that makes decisions which will ultimately impact the lives of people to be implemented, Miller (2021) argued the developers of the corresponding programs and procedures should be considered moral agents and thus should seek to minimize harm and abide by the moral standards of society. Therefore, it can be inferred that a major challenge to the implementation of AI systems is accountability. It is certain that no algorithmically generated decision should be implemented without a sufficient degree of human oversight, but within this limitation, there is a lack of clarity regarding who would be responsible for any consequences therein.

4.6 Continuous Maintenance and Updates

Software, much like hardware, is a resource that must be maintained and improved upon regularly. The need to carefully plan and implement the rollout of software updates is a common challenge faced in an increasingly technology-dependent world. Kaur and Singh, (2015) noted that the maintenance costs associated with software often stem from improvements rather than corrections, and there are a range of challenges inherent to this process, from estimation to implementation to impact analysis. In the case of machine-learning technology such as AI, which is highly valued for its capacity for self-improvement, it can thusly be inferred that a major component to post-launch support would potentially be continuous quality assurance to guarantee that performance remains within the desired standards.

5. Companies That Have Implemented AI in Project Management

Companies across various industries are integrating AI into project management to streamline workflows, enhance decision-making, and improve overall efficiency. By leveraging AI-driven automation, predictive analytics, and intelligent resource allocation, companies can optimize project execution and minimize risks. This section examines how leading organizations are successfully implementing AI to transform their project management practices and achieve strategic advantages.

5.1 PwC AI-Driven Business Transformation

According to a recent report by PwC (n.d.), PricewaterhouseCoopers (PwC), a global leader in professional services, providing consulting, assurance, and tax advisory solutions to businesses across industries, has integrated AI into its business transformation initiatives through SAP, utilizing machine learning and predictive analytics to streamline financial planning, supply chain management, and customer service. AI-powered forecasting tools help PwC anticipate financial risks and optimize budget allocation, ensuring projects remain on track. Additionally, AI-enhanced supply chain management enables real-time tracking of materials, demand forecasting, and automated inventory control, reducing bottlenecks and minimizing operational delays. In customer service, AI chatbots and automated reporting improve client interactions by providing instant responses and data-driven recommendations, enhancing overall project efficiency and strategic alignment.

5.2 Bechtel: AI in Megaprojects

As reported by Garza (2018), Bechtel, a global leader in construction and engineering, applies AI in megaprojects to improve project execution and risk management. The company employs deep learning models for construction sequencing, which enhances scheduling accuracy and reduces site density issues by optimizing workforce distribution and material flow. AI-powered predictive analytics also help Bechtel identify potential delays and safety risks, allowing for proactive mitigation strategies. By leveraging AI, Bechtel improves project timelines, minimizes rework, and enhances overall cost-effectiveness in complex infrastructure projects.

5.3 Willmott Dixon: AI-Driven Automation in Construction

Moss (2025) discussed Willmott Dixon, a UK-based construction and property services company, that has embraced AI-driven automation to streamline project workflows, minimize human error, and optimize resource allocation. AI-powered tools assist in project scheduling, labor management, and material tracking, ensuring efficient use of resources and reducing waste. The company also invests in training its workforce to adapt to AI innovations, fostering a culture of digital transformation. AI-assisted quality control processes help detect defects early, reducing costly rework and improving project outcomes.

These applications demonstrate how AI is transforming project management through automation, enhanced decision-making, and improved resource management.

6. AI Implementation Roadmap

The AI Implementation Roadmap outlined by Reim et al. (2020) presents a structured four-step framework for integrating artificial intelligence (AI) into business model innovation (BMI). The first step, Understanding AI and Organizational Capabilities, involves assessing the firm's readiness for digital transformation by evaluating existing capabilities and identifying gaps in strategic, technological, data, and security infrastructure. The second step, Understanding the Current Business Model and Potential for BMI, requires analyzing how value is currently created, delivered, and captured, and determining how AI can enhance these processes within the business ecosystem. The third step, Developing and Refining Capabilities, focuses on building technical expertise, data infrastructure, and security measures while addressing challenges like transparency and operational alignment. Finally, the fourth step, Reaching Organizational Acceptance and Developing Competencies, emphasizes securing employee buy-in through pilot projects, AI training programs, and the formation of AI-expert teams to ensure stakeholders understand AI's role and value within the organization. This roadmap serves as a strategic guide for businesses to effectively implement AI and drive competitive advantage through business model innovation.

7. Conclusion

Future trends and innovations in AI for project management focus on enhancing decision-making, automation, and predictive capabilities through emerging technologies such as generative AI and machine learning. Generative AI is increasingly being used to simulate project scenarios, automate strategic planning, and develop innovative project solutions. Machine learning models, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), are being applied to predict project costs, timelines, and risks with greater accuracy. Additionally, AI-powered natural language processing (NLP) is improving communication and stakeholder engagement by automating report generation and facilitating real-time updates. Tools like ChatGPT are being integrated into project workflows to enhance documentation and communication efficiency. Furthermore, AI is playing a crucial role in optimizing resource allocation and improving risk management by analyzing historical data and providing actionable insights. As AI adoption increases, the combination of machine learning, data science, and real-time monitoring is expected to further refine project management processes, driving greater efficiency and strategic alignment in complex project environments.

In conclusion, the integration of AI into project management offers transformative potential, enhancing efficiency, decision-making, and quality. However, significant challenges, including data quality, technical barriers, resistance to change, and ethical considerations, must be addressed to fully harness its benefits. Organizations aiming to implement AI in project management should invest in skilled personnel, robust data governance, and adaptable AI systems to navigate these challenges effectively. Future research should focus on developing comprehensive frameworks to map AI tools and challenges, providing actionable solutions that advance the adoption of AI in project management.

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TRUST IN AUTOMATION: EXAMINING THE RELATIONSHIP WITH DECISION-MAKING AMONG AUTOMOBILE DRIVERS IN THE UNITED STATES

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Abstract

The main objective of the study was to examine the relationship between trust in automation on decision-making with respect to automobile drivers in the United States (U.S.). Human errors currently contribute to 93% of crashes in the U.S. Autonomous vehicles have the potential to significantly decrease the number of accidents caused by human error. The level of trust drivers place in automation plays a crucial role in shaping their decision-making processes. A sample of N = 174 adult drivers in the U.S. responded to an online survey. The appropriate research methodology for the current study was explanatory correlational. A bivariate regression analysis revealed a significant and positive association between trust in automation and decision-making scores of automobile drivers in the U.S. The current research plays an important role in establishing the critical link between trust in automation and decision-making among adult drivers and emphasizes the essential requirement of not only ensuring effective functionality in automated systems but also fostering user trust. The current research addressed multiple strategies to original equipment manufacturers: (a) developing training programs to educate drivers about automation, (b) designing driver-centered automation interfaces that communicate effectively and (c) designing systems that ensure consistent performance.

Keywords: *Trust in Automation, Decision Making, Human Computer Interactions, Autonomous Vehicles, Automobile Drivers, and Adoption of Automation.*

1. Introduction

According to the National Highway Traffic Safety Administration (NHTSA, 2023), between 2013 and 2022 there were 374,271 fatal motor vehicle accidents in the United States (U.S.). Of those, 94% were caused by human error (National Highway Traffic Safety Administration [NHTSA], 2023). According to Szatmáry and Lazányi (2024), self-driving vehicles have the capability to reduce human errors and improve road safety. Self-driving vehicles, also known as autonomous vehicles (AV) have the potential to significantly decrease the number of accidents caused by human error in the U.S. when compared to conventional manually operated vehicles (Du et al., 2021; Xu et al., 2018). Society of Automotive Engineers (SAE, 2016) classified vehicle autonomy into six levels: Level 0: no automation, Level 1: driver assistance, Level 2: partial automation, Level 3: conditional automation, Level 4: partial automation, and Level 5: full automation. Self-driving or autonomous vehicles are designed to help human drivers in their decision-making process by decreasing their workload, enhancing their situational awareness,

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and therefore, decreasing the human errors. According to Du et al., (2021), the autonomous vehicle market is projected to cross $20 billion by the end of next decade (2030-2040).

Although the AV market appears to be growing at an exceedingly frequent rate, the acceptance of autonomous vehicles differs among people based on various factors. Many researchers in the past have found that several constructs such as personality traits, perceived usefulness, perceived safety risk, and trust in automation have to found to influence people's acceptance of autonomous vehicles (Benleulmi & Blecker 2017; Kaur & Rampersad, 2018; Namukasa et al., 2023; Payre et al., 2014; Xu et al., 2018). Studies in the past have also focused on understanding the relevance of trust in human-automating teaming (Carmody et al., 2024, Duan et al., 2024). The integration of automation in various aspects of our daily lives has significantly affected the way people make decisions. In the context of the automobile industry, the level of trust drivers place in automation plays a crucial role in shaping their decision-making processes. Therefore, the main purpose of the current study was to investigate the relationships of trust in automation and decision-making with respect to automobile drivers in the United States (U.S.).

1.1 Research Question and Hypothesis

1.1.1 Research Question

What is the relationship between trust in automation and decision-making with respect to automobile drivers in the U.S.?

1.1.2 Research Hypothesis

It is hypothesized that trust in automation is going to have a positive relationship with decision-making among automobile drivers in the U.S.

2. Background

The following background includes a literature review of past empirical studies aimed at further exploring the relationship between trust in automation and its impact on decision-making. This impact is examined in terms of reducing workload, enhancing situation awareness, and aiding individuals in safety behaviors in both automobile and non-automobile domains. Luster and Pitts (2021) investigated the relationships of system certainty on trust in automation and decision-making time among engineering graduate students at Purdue university. Luster and Pitts used a sample of $N = 11$ participants of that seven were male and four were female. The results indicated that decision making time was significantly $F(3,30) = 5.984$, $p = .003$, $\eta 2 = .373$) higher when the system certainty was low. In addition to that the participants also rated a higher trust in system was the system certainty was higher. In another study, Metzger and Parasuraman (2017) investigated the relationships of automation on the shared decision-making responsibilities between air traffic controllers and pilots in future air traffic management. Metzger and Parasuram (2017) conducted a study to explore the relationships of automation on air traffic controllers' mental workload and performance. A sample of $N = 12$ participants from the Washington D.C.'s, Air Route Traffic Control Center (ARTCC) took part in the experiment with a $M = 37.65$ years and $SD = 5.05$ years. One of the major objectives of Metzger and Parasuram's study was to investigate whether automation can reduce decision conflict during high workload conditions. The results indicated that automation had a significant relationship on decision conflict ($F (3, 57) = 6.28$, $p <.01$.), where automation helped controllers by lower their decision conflict.

In another study Rodriguez et al., (2021) explored the relationship between dynamics of trust in automation and decision-making during driving. The study was conducted using a driving simulator where a sample of $N = 16$ participants with a $M = 26.10$ years and $SD = 8.01$ years took part in the study. Rodriguez et al. manipulated the automation with two levels: low and high. The study had twofold objectives: (a) factors influencing drivers trust in automation, and (b) factors influencing drivers' decision making. The results indicated that the level of automation significantly influenced drivers' trust in automation. The findings indicated that high levels of automation lead to an increase in drivers' trust in automation. The findings also revealed that drivers' trust in automation also positively influenced their decision-making skills. Li et al., (2019) investigates the relationships of age and disengagement in driving on drivers' takeover control performance in highly automated vehicles (HAV). The study used a sample of N = 76 young and old drivers, who took part in a simulation study. After the HAV disengagement, older drivers took longer to take over control when compared to the younger drivers. The results also indicated that older drivers exhibit longer response times when taking over control from the HAV, particularly after engaging in non-driving tasks. Age is a big factor in determining how older people compared to younger people react to automation.

Loft et at., (2021) conducted a study to examine the impact of automation transparency on the decision-making of unmanned vehicle operators. A total of N = 180 undergraduate students from University of Western Australia took part in this study. Out of 180 participants, 36.4% of them were male and the remaining 64.6% participants were female. The results indicated that there was no significant relationship of automation transparency on the decision-making of unmanned operators $F(1,114) = 1.80$, $p = .18$ 9 (Loft et al., 2018). However, the results did identify a significant interaction between automation transparency and decision risk on the decision-making of student participants $F(1, 114) = 8.37$, $p = .005$, $\eta 2 = .07$ (Loft et al., 2018). The findings suggested that for high-risk conditions, the participants had less trust in automation advice and therefore impacted their decision time. Additionally, the findings also revealed that high automation transparency increased the trust of unmanned vehicle operators on automation and therefore reduced the decision time.

In summary, multiple studies from the current studies literature review shed light on the relationship between trust in automation on decision-making across domains such as air traffic control, driving with assistance systems, and semi-autonomous vehicles. The findings from past studies also signify the complexity of factors influencing decision-making dynamics, including the role of non-driving tasks, transparency, and the acceptance of automation in high-risk scenarios. As we propel through these nuanced relationships, it is evident that a critical gap exists in our understanding, particularly concerning the relationships of trust in automation on decision-making among autonomous vehicle drivers. By specifically focusing on automobile drivers in the United States, the current study seeks to provide targeted insights into the relationship between trust in automation and decision-making within this demographic.

3. Methods

3.1 Research Methodology

The current study used a correlational research methodology with an explanatory research design. Explanatory correlational was an appropriate research methodology for the current study, because we investigated the relationship between trust in autonomation and decision-making with respect to a single group, that is, automobile drivers in the U.S. Based on Ary et al.'s (2010) suggestion, a correlational research methodology helps identify relationships among multiple variables, with respect to a single group. The current study contained one independent variable (IV): trust in automation and one dependent variable (DV): decision-making of automobile drivers.

3.2 Power Analysis

An a priori analysis was conducted to determine the minimum sample size needed, using G* Power (Faul et al., 2007, Gallo et al., 2023). An a priori analysis for an F-test, using a bivariate regression was conducted. Power analysis parameters included an $\alpha = 0.05$, with a medium relationship size of Cohen's f 2 = .15 (Cohen, 1988), and a minimum power (1 – β) of 80%. Based on G*Power results, it was found that a minimum sample size of N* = 55 participants was required to have a power of 80% power with a medium relationship in the population.

3.3 Population and Sample

The target population for the present study encompasses all adult individuals in the United States who are 18 years of age or older and drive four-wheeled vehicles. From the target population, a non-random sampling strategy was utilized to recruit participants. More precisely, a convenience sampling strategy was used to obtain participants for the current study. As reported in Table 1, 97 (55.4%) were male adult drivers and the remaining were females 76 (43.4%). The mean age for female adult drivers was M = 36.7 years (SD = 14.3), male adult drivers was M = 39.9 years (SD = 14.6), and on average male adult drivers were 3 years older than females.

Table 1. Summary of Participants' Age by Biological Sex

Biological Sex[a]	Age			
	N	**M**	**SD**	**R**
Female	76	36.7	14.3	18–66
Male	97	39.9	14.6	19–79
Overall	174	38.5	14.5	18–79

Note. *N* = 174. [a]One participant did not report biological sex.

As reported in Table 2, 37 (21.3%) of the overall sample of N = 174 participants, were female participants, who drove less than five hours a week, and 35(20%) of the overall sample of N = 174 participants of them were male drivers who also drove less than five hours a week.

Table 2. Summary of Weekly Driving Hours by Biological Sex

Biological Sex	**Driving Hours Per Week**[b]									
	<5		**5 to 10**		**11 to 15**		**16 to 20**		**>20**	
	N	***%***	***N***	***%***	***N***	***%***	***N***	***%***	***N***	***%***
Female	37	21.3	29	16.6	6	3.4	3	1.7	1	0.6
Male	35	20.0	39	22.3	15	8.6	3	1.7	5	2.9
Overall	73	41.7	68	38.9	21	12.0	6	3.4	6	3.4

Note. *N* = 174. [b]The percentages reported for the Overall group are with respect to overall sample size of *N* = 174.

3.4 Human Subjects Research

The present study involved collecting data from human subjects who were adult drivers in the U.S. and hence was considered human subjects' research. Therefore, an application to Florida Institute of Technology's Institutional Review Board (IRB) was submitted. I was the only data collector for the current study. My co-authors and I were the only individuals who had access to the data. All the participants in the current study were recruited voluntarily. All the participants were free to leave the study at any point during the survey. Participants identifying information was kept separate from their data to ensure anonymity. All the participants were notified of the risk involved by participating in this survey, which should not be more than the risk one could encounter while interacting with a computer or any electronic device. All the demographic information obtained from the participants was kept confidential.

3.5 Study Implementation

The current studies data was collected using a single data collection questionnaire with multiple sections that included a demographic section where participants reported their age, biological sex assigned at birth, and total driving hours in a week. Jian et al.'s (2000) system trust scale (STS) was used to measure participants' trust in automation, and a researcher modified version of French et al.'s

(1993) decision-making questionnaire (DMQ) was used to measure participants decision-making. The questionnaire was delivered via Qualtrics. Before beginning the primary data collection, we conducted a preliminary study to assess the reliability and face validity of the instruments. To give attention to instrument reliability and validity, we calculated and presented Cronbach's alpha in Table 3. After building the questionnaire, we had a subject matter expert review the items and ensure that adequate attention was given to the face validity in terms of the content and flow of the instruments in the survey. After identifying the accessible population from the target population, all the participants for the current study were recruited via email and other platforms using a convenience sampling strategy. All the participants were emailed a link to the Qualtrics survey along with instructions to complete the survey. All the descriptive and inferential analysis was conducted on JMP.

Table 3. Reliability Coefficients

Instrument			Cronbach α	
	M	***SD***	**Current Study**	**Reported**
STS	35.4	5.27	.77	.89
DMQ	46.5	6.11	.80	.73

4. Results

This part of the paper presents the results of the current study and is divided into two sections. The first section presents a summary of descriptive statistics of both the independent and dependent variables including trust in automation and decision-making by biological sex and age. The second part presents the results of the inferential statistics through linear regression. As part of the regression analysis, the results of the omnibus analysis and the regression estimate are also presented.

4.1 Descriptive Statistics

As summarized in Table 4, drivers scored high on trust in automation. The overall scores ranged from 10 to 49, with a mean score of M = 35.4 (SD = 5.27). When the trust in automation was examined by biological sex, females (M = 35.2, SD = 4.94) had a slightly lower trust in automation compared to males (M = 35.6, SD = 5.56). As summarized in Table 4, drivers also scored high on decision-making. The overall scores ranged from 8 to 56, with a mean score of M = 46.5 (SD = 6.11). When decision-making was examined by biological sex, females (M = 46.7, SD =5.81) decision-making scores were similar to those of males (M = 46.4, SD =6.33).

Table 4. Summary of Driver' Trust in Automation and Decision-making by Biological Sex

		TIA[b]				DM[c]		
Sex[a]	***N***	***M***	***SD***	***Range***		***M***	***SD***	***Range***
Male	97	35.6	5.56	10–47		46.4	6.33	8–56
Female	76	35.2	4.94	21–49		46.7	5.81	28–56
Total	174	35.4	5.27	10–49		46.5	6.11	8–56

Note. *N* = 174. [a]One participant did not report gender. [b]TIA = Trust in automation. [c]DM=Decision-making.

As shown in Figure 1, the average trust in automation scores of male participants was higher than those of female participants when driving hours were between 5 to 10 hours a week and 16 to 20 hours a week.

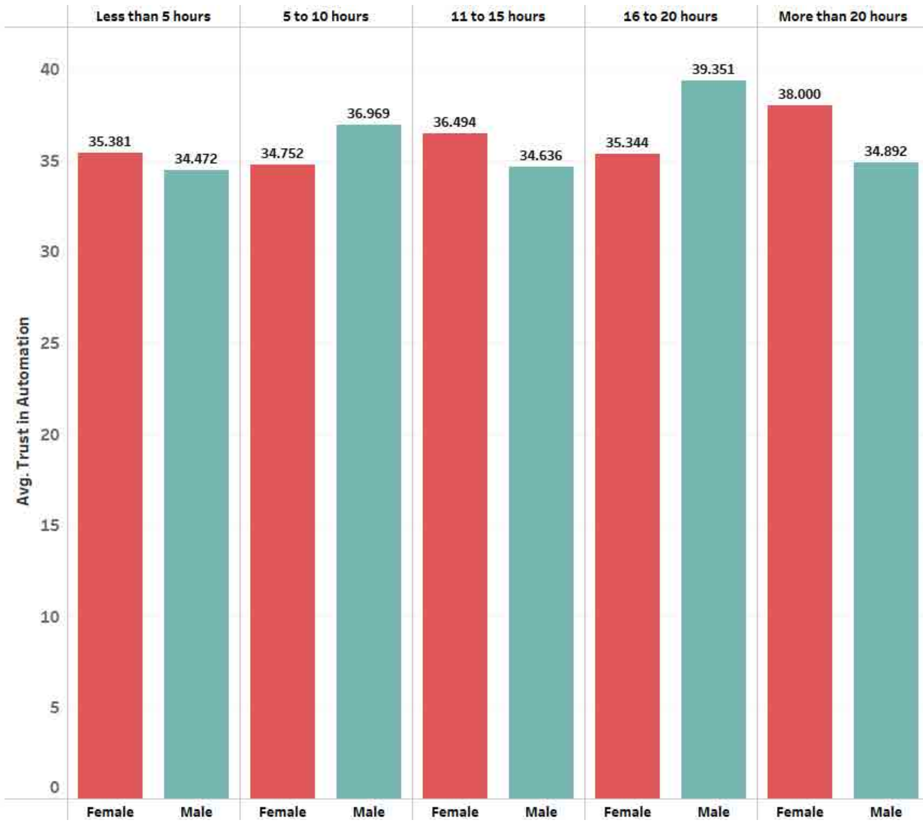

Figure 1. Average Trust in Automation Scores based on Biological Sex and Weekly Driving Hours

However, female participants' scores indicated a higher trust in automation when the driving hours were less than five hours a week, 11 to 15 hours a week, and more than 20 hours a week. The data suggests that male participants generally project higher trust in automation during specific weekly driving hours, while female participants show higher trust in automation at other intervals, highlighting gender-related variations in trust perceptions. As shown in Figure 2, male participants tend to have higher decision-making scores compared to female participants when they drive more than 16 hours a week, whereas female participants exhibit higher decision-making scores than men when driving between 11 to 15 hours a week.

4.2 Inferential Statistics

4.2.1 Preliminary Analysis

An outlier analysis was conducted using Jackknife distance to investigate for any potential outliers in the sample that would adversely influence the results of the current study. According to Gallo et al., (2023), outliers could be a result of contaminated data, or they could just be rare case. In the current study, we found 4 cases that were above the upper control limit (UCL) of the Jackknife distances plot. An independent examination for each outlier was performed to see if the data was an extreme case or a corrupted value. Of the four cases, we determined 0 cases which were contaminated and decided to keep the extreme cases in the dataset, and the total size of the final dataset was N = 174. Before running the model, we tested and met all the four assumptions of bivariate regression: Linearity, Homoscedasticity of residuals, independence of residuals, and normality of residuals.

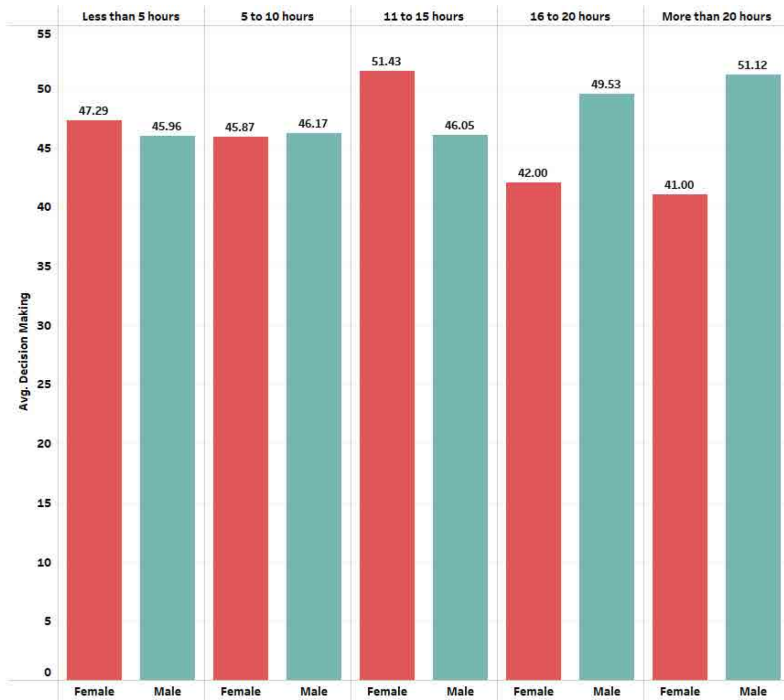

Figure 2. Average Decision-Making Scores based on Biological Sex and Weekly Driving Hours

4.2.2 Primary Analysis

Based on Gallo et al.'s (2023), a bivariate regression was conducted using the Y = Decision-making among automobile drivers as a dependent variable and X = Trust in Automation as an independent variable. As reported in Table 5 when Y = Decision-making was regressed on X = Trust in Automation, 6.3% of the variance in automobile drivers' Decision-making was explained by their Trust in Automation. In other words, if we know the automobile drivers' trust in automation score, then we will have 6.3% of the information to accurately predict their decision-making. The contribution made by Trust in Automation in explaining the variance in Decision-making was significant, R2 = .063, F(1, 172) = 11.69, p < .001. As the omnibus was significant, we examined the relationship between Trust in Automation and Decision-making among automobile drivers in the U.S.

Based on the regression analysis reported in Table 5, the prediction equation for the model was found to be $\hat{Y}$= 0.29X + 36.20. The relationship between trust in automation and decision-making was positive and statistically significant at the pre-determined alpha level of .05, B = 0.29, t(172) = 3.42, p <.001: for every 1-point increase in the Trust in Automation score of automobile drivers, on average, the scores on decision-making increased by 0.3units. Therefore, based on this finding, it appears that automobile drivers who score high trust in vehicle's automation are likely to make better decisions while driving.

Table 5. Summary of Bivariate Regression Analysis

Variable	*B*	*95% CI for B*		*SE B*	*t*	R^2
		LL	*UL*			
Y = Decision-making						*.063****
Constant	*36.20****	*30.15*	*42.26*	*3.06*	*11.80*	
X = Trust in Automation	*0.29****	*0.12*	*0.46*	*0.08*	*3.42*	

Note. *N* = 174. * *p* < .05, ** *p* < .01, *** *p* < .001.

4.2.3 Post-hoc Power Analysis

According to Gallo et al., (2023) guidelines a post-hoc relationship size for the current study was calculated and was found to be 0.064, which according to Cohen (1998) is considered as a small relationship size. As reported in Table 5 the 95% confidence interval (CI) for B was [0.12, 0.46], which tells us that 95% of the time we can expect, for every 1-unit increase in the Trust in Automation score among automobile drivers in the US, the decision-making score on average will increase anywhere between 0.12 and 0.46. A post-hoc power analysis was conducted to determine the approximate power of the study on G* power software with the following parameters: significance level of $\alpha = 0.05$, with a small relationship size of Cohen's $f\ 2 = .064$ (Cohen 1988), sample size of $N = 174$. The software returned a power of 0.9128, which indicates there is 91.3% probability that the small relationship found in the sample truly exists in the population.

5. Discussion

The research aimed to explore the impact of Trust in Automation on automobile drivers' Decision-making. The findings of the current study based on the regression analysis indicated a statistically significant relationship between trust in automation and decision-making. The positive coefficient ($B = 0.29$) indicates that there is a positive association between trust in automation and decision-making scores among automobile drivers in the U.S. The findings of the present study also align with the research hypothesis indicating that automobile drivers who have a higher level of trust in automation are more likely to enhance the decision-making capabilities of automobile drivers. The findings of the current study also were consistent with research conducted in the past indicating that trust in automation positively influences various aspects of behavior and decision-making processes (Loft et al., 2021). Various studies in the past have reported the important role of drivers' trust in their usage of highly automated systems. Few studies in the past have also found that individuals with higher trust in automation are more likely to use automation and therefore, project good decision-making abilities (Loft et al., 2021). The current study's findings further validate and extend these findings by emphasizing the direct impact drivers' trust has on their decision-making abilities.

The implication of the present study's findings is muti-fold. The first implication underscores the importance of drivers' trust in automation as a key construct in determining their decision-making abilities. The findings from the present study also directs the attention of original equipment manufacturers towards constructing autonomous systems that are not only robust in operations but also cultivate trust among drivers and help them in their decision-making process. Therefore, designing an autonomous system that is capable of nurturing trust among drivers would also significantly help their decision-making abilities, especially in dynamic traffic conditions. For instance, designing systems that alert drivers with multi-modal cues, such as audio, verbal, and haptic, is more likely to enhance their trust.

The second implication is that the original equipment manufacturers should also focus on designing autonomous systems that are integrated with strategies that would improve drivers' trust. For example, when drivers engage in autopilot mode in dynamic traffic conditions, the system may detect an obstacle and decide to slow down by engaging the brakes. A robust system would not only perform this maneuver but also communicate the process to the driver and yield control to them to make the final decision. An autonomous system designed with high level of reliability, transparency, and effective communication is more likely to bolster the confidence and trust among automobile drivers towards automation.

The third implication is that by understanding the relationship between trust in automation and decision-making, autonomous vehicle manufacturers could design training programs to enhance drivers' trust in automation capabilities. For example, policy makers along with manufacturers could develop training programs by incorporating strategies such as short simulation-based guided training before delivering a new car. Policy makers along with manufacturers could also implement mandatory annual or bi-annual assessments of human vehicle interactions through simulation-based testing. The incorporation of these techniques could bolster drivers' trust in automation, consequently, positively influence their decision-making abilities.

The final implication signifies the need for original equipment manufacturers to transparently communicate to the consumers about their automation models and methods. They need to provide clear disclosure on how their automation models have been created and explain why their models make the predictions and recommendations they do under certain scenarios. For instance, when the autonomous system aids the driver's decision-making process in a dynamic traffic scenario by predicting a lane change 500 feet ahead due to a stalled vehicle, it becomes essential to provide drivers with a clear and comprehensive explanation of how the autonomous system made that prediction. This commitment to transparency enhances users' understanding of the capabilities of autonomous systems and reduces the existing trust gap, which in turn influences the decision-making abilities of drivers.

5.1 Limitations and Delimitations

According to Ary et al., (2009), limitations and delimitations are conditions that a researcher has no control over and chooses to impose in their study respectively, that will limit the generalizability of the study's result. Therefore, the reader is advised to consider any conclusions or inferences derived from the present study's results with respect to the limitations and delimitations provided below. All the participants voluntarily took part in this study. As a result, there was no control over the participants' personological characteristics such as age, biological sex, and number of hours they drive every week. The present study's findings may not be generalizable to a similar study conducted with different sample demographics. The current study was administered through an online Qualtrics survey, and we had no control over participants' response rate. As a result, similar studies that use a different data collection approach such as survey monkey, or paper surveys may have more, or fewer participants and may yield non-identical findings.

The current study used standardized data collection instruments. The standardized instruments included system trust scale (STS) and decision-making questionnaire (DMQ). As a result, a study that use other instruments are likely to yield different findings. Although the current study collected demographic information related to automobile drivers such as age, biological sex, and numbers of hours they drive in a week it did not control them or include them in the analysis. As a result, a similar study that controls the relationship of these variables or includes them in their model might get different results. The current study used a non-random probability sampling strategy. All the participants voluntarily took part in the current study. Therefore, a similar study with a different sampling strategy might yield different results.

6. Conclusions

In conclusion, the current research establishes the crucial link between trust in automation and decision-making among automobile drivers. The results indicate a positive impact, with 6.3% of decision-making variance explained by trust in vehicle automation. The study highlights the necessity of not only ensuring effective functionality in automated systems but also fostering user trust. The observed positive relationship also suggests that interventions and training programs targeting increased trust in automation could positively affect decision-making skills among automobile drivers.

The current research addressed the need for diverse strategies that would cultivate trust among automobile drivers towards autonomous vehicles and therefore, assist them in their decision-making process. This involves building training programs that enhance the awareness among drivers about automation while promoting balanced trust and decision-making skills. Original equipment manufacturers should focus on designing user-centered automation interfaces that will not communicate effectively with the drivers, but also ensure consistent performance. Policymakers along with manufacturers can use these insights to create guidelines prioritizing trust and decision-making in automation ensuring reliability and safety. This holistic approach—design innovation, training programs, and regulatory policies—will aim to enhance drivers' trust in automation. The suggested approach could also improve drivers' decision-making abilities, leading to a safe adaptation of automation in driving and related domains.

Future studies should focus on how individual differences, such as personality traits and affective domain variables, impact the relationship between trust in automation and decision-making. Exploring demographic factors such as education and technological familiarity can also provide insights into this relationship. Advanced techniques like neuroimaging may provide a deeper insight into the neural processes involved. Furthermore, investigating the broader socio-cultural factors influencing the relationship of trust and decision-making among automobile drivers is crucial to understand their impact on automation adoption. A comprehensive exploration of these dimensions will contribute to a more detailed understanding of the intricate dynamics in the context of automated transportation.

7. Disclaimer Statements

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Conflict of Interest: None

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EVOLUTION OF EMPLOYEE 4.0: PERSPECTIVES ON TECHNOLOGY IN HOSPITALITY

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Abstract

This study investigates the evolution of Employee 4.0 within the hospitality sector, focusing on professionals' experiences and perspectives on technology. While few professionals mentioned technology, those who did expressed concerns about potential job displacement and the impact of automation. This fear reflects a broader apprehension within the industry about the integration of advanced technologies and their implications for traditional roles and job security. Conversely, participants outside the hospitality sector viewed technology as an essential tool for success and growth, highlighting its benefits in enhancing efficiency, productivity, and customer satisfaction. These external perspectives underscore a contrast in how technology is perceived and embraced across different sectors.

By analyzing these divergent viewpoints, the study provides valuable insights into the challenges and opportunities associated with Employee 4.0 in the hospitality industry. It highlights the need for targeted strategies to address the concerns of hospitality professionals, foster a positive attitude towards technological advancements, and ensure a balanced approach that leverages technology to enhance service quality while preserving the human touch that defines the industry. This comprehensive analysis contributes to the ongoing discourse on the future of work in the hospitality sector and offers practical recommendations for industry stakeholders to navigate the evolving landscape of Employee 4.0.

Keywords: *Employee 4.0, Hospitality Industry, Technology, Automation, Job Displacement, Professional Perspectives, Sectoral Differences, Technological Integration, Future of Work, Human Touch*

1. Introduction

The hospitality industry has always been a dynamic and evolving sector, constantly adapting to changing customer needs and technological advancements. With the advent of Industry 4.0, characterized by the integration of digital technologies such as artificial intelligence, the Internet of Things (IoT), and big data analytics, the role of employees in this sector has undergone a significant transformation. This paper aims to explore the evolution of Employee 4.0 within the context of the hospitality industry, focusing on how technological advancements have reshaped employee roles, experiences, and leadership. By examining the perspectives of professionals within and outside the hospitality sector, this study provides valuable insights into the challenges and opportunities associated with Employee 4.0.

The integration of advanced technologies in the hospitality sector has sparked a range of

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reactions among professionals (discussed in results section). While some view technology as an essential tool for success and growth, enhancing efficiency, productivity, and customer satisfaction, others express concerns about potential job displacement and the impact of automation. This fear reflects a broader apprehension within the industry about the integration of advanced technologies and their implications for traditional roles and job security. Conversely, participants outside the hospitality sector highlight the benefits of technology in enhancing efficiency, productivity, and customer satisfaction. These external perspectives underscore a contrast in how technology is perceived and embraced across different sectors. By analyzing these divergent viewpoints, the study provides valuable insights into the challenges and opportunities associated with Employee 4.0 in the hospitality industry

In conclusion, the evolution of Employee 4.0 within the hospitality industry is a multifaceted phenomenon that requires a comprehensive understanding of technological advancements, employee experience, and leadership. This paper aims to bridge the gap in literature by providing insights into how Industry 4.0 principles can be applied to optimize employee experience in hospitality, ultimately contributing to the success and sustainability of organizations in this sector. By examining the perspectives of professionals within and outside the hospitality sector, this study provides valuable insights into the challenges and opportunities associated with Employee 4.0. The findings from this research highlight the dual nature of technology's impact on employee experience in the hospitality industry, emphasizing the need for targeted strategies to address the concerns of hospitality professionals, foster a positive attitude towards technological advancements, and ensure a balanced approach that leverages technology to enhance service quality while preserving the human touch that defines the industry.

2. Methodology – Literature Review

This review was planned, conducted, and reported in adherence to the preferred reporting items for systematic reviews and meta-analyses (PRISMA). These guidelines help researchers transparently display findings via the results of a systematic literature review, infusing transparency, quality, consistency and credibility into the process (Moher et al., 2009). This study aimed to answer the following research question:

RQ1: How has technology changed the landscape in hospitality and how do hospitality employees feel about technology in their industry?

To examine the literature on employee 4.0 and technology, papers from a wide array of industries were examined from peer-reviewed journals. Databases and searching platforms used include Inspec, Compendex, EBSCOhost (many DBs but primarily Business Source Premier), Google Scholar, and Web of Science.

Articles were subdivided into three sections, depending on the content, to address the research questions. The sections are classified as follows.

1. Articles regarding employee 4.0 in general
2. Articles regarding employee 4.0 and technological advancements
3. Articles regarding hospitality

3. Literature Review

The rapid advancement of technology has significantly transformed various industries, including hospitality. This section explores the concept of Employee 4.0 within the hospitality sector, examining how technological advancements have reshaped employee roles, experiences, and leadership. The review highlights the unique challenges faced by hospitality employees and the importance of job crafting in navigating these changes.

The concept of Employee 4.0 is rooted in the broader framework of Industry 4.0, which emphasizes the integration of digital technologies to enhance productivity, efficiency, and innovation. Employee 4.0 refers to the evolving role of employees in this digital era, where they are expected to actively craft their work lives and adapt to the accelerating pace of change in both internal and external environments (Wrzesniewski & Dutton, 2001). In the hospitality industry, employees face unique challenges in catering to a diverse group of customers while achieving organizational effectiveness (Chen, Yen, & Tsai, 2014; Kim, Im, Qu, & NamKoong, 2018). Technological advancements play a crucial role in enabling real-time experiences and reducing role stress for hospitality employees (Cheng & O-Yang, 2018).

Technological advancements in the hospitality industry span a wide spectrum, from inventory browsing to comprehensive online reservation and purchasing services (Shamim, Cang, Yu, & Li, 2017). While these advancements offer vast information and usability on a single platform, they also demand employees exhibit flexibility, dynamic capabilities, and innovative behavior (Yadav, 2020). Front office roles are particularly influenced by these changes, requiring employees to develop new competencies, such as social intelligence and creativity, to keep pace with technological advancements (Yadav, 2020; Res, Wild, Sthal & Baudet, 2017 as cited in Yadav, 2020).

Artificial intelligence (AI) technologies are redefining the hospitality industry, impacting employee engagement, productivity, and retention (Ruel & Njoki, 2021). This research highlights the importance of understanding the role-service-profit chain, which links employee factors such as engagement and retention to outcomes like quality and customer satisfaction, ultimately improving the bottom line. AI-driven talent management practices can significantly influence the employee experience and overall business performance.

While much of the literature on Industry 4.0 focuses on technological aspects, it is essential to consider the interplay between management practices and employee development. Studies have shown that appropriate management techniques can foster dynamic employee capabilities and an effective learning and innovation environment (Shamim, Cang, Yu, & Li, 2017). In the hospitality industry, employee experience is critical as customer expectations continue to rise. Employees must meet and exceed these expectations to maintain and improve customer satisfaction, loyalty, and service quality (Shamim, Cang, Yu, & Li, 2017).

The accelerated pace of change has resulted in less clearly defined work roles, necessitating a proactive approach from employees to reshape their positions (Demerouti, Bakker, & Gevers, 2015). To thrive in a dynamic environment, hospitality employees must leverage technological advancements that facilitate real-time experiences and mitigate role stress (Cheng & O-Yang, 2018 as cited in Yadav, 2020). This proactive approach, known as job crafting, involves employees making physical, relational, and cognitive changes to their roles (Wrzesniewski & Dutton, 2001 as cited in Yadav, 2020).

The intersection of Employee 4.0 and Industry 4.0 provides a framework for leveraging leadership as a critical component of employee experience, emphasizing the need for next-generation leadership competencies such as cognitive readiness, critical thinking, and emotional and social intelligence (Bawany, 2017). Literature on leadership in Industry 4.0 underscores the managerial challenges posed by technological disruptions and the role of leaders in guiding their teams through these changes (Bawany, 2017).

Despite the growing interest in Employee 4.0, literature specifically addressing its application in the hospitality industry remains sparse. An extensive search for relevant sources reveals a lack of depth in studies combining Employee 4.0 and hospitality, indicating an opportunity for new research to contribute to this field.

In conclusion, the evolution of Employee 4.0 within the hospitality industry is a multifaceted phenomenon that requires a comprehensive understanding of technological advancements, employee experience, and leadership. This paper aims to bridge the gap in literature by providing insights into how Industry 4.0 principles can be applied to optimize employee experience in hospitality, ultimately contributing to the success and sustainability of organizations in this sector.

3.1 Evolution of Employee 1.0 to Employee 4.0

The concept of Employee 4.0 represents a significant shift in the role and expectations of employees within the context of Industry 4.0. This evolution can be traced through four distinct phases, each characterized by different attributes and responsibilities (Haijian & Fangfang, 2018).

3.1.1 Employee 1.0: Subordinates with Little Initiative

In the earliest phase, Employee 1.0, employees were primarily seen as subordinates who followed orders with minimal initiative. Their roles were largely defined by obedience and adherence to instructions from their superiors. This period was marked by a hierarchical structure where employees had limited autonomy and were expected to perform tasks as directed without questioning or contributing to decision-making processes (Haijian & Fangfang, 2018).

3.1.2 Employee 2.0: Self-Managers and Strategic Business Units

The transition to Employee 2.0 brought about a shift towards self-management (Haijian & Fangfang, 2018) while industry 2.0 itself ushered in electricity (Oberer & Alptekin, 2018). Employees began to take on more responsibility and were seen as strategic business units within the organization. This phase emphasized the importance of employees managing their own work and contributing to the strategic goals of the company. Employees were encouraged to be proactive, take initiative, and make decisions that aligned with the organization's objectives (Haijian & Fangfang, 2018).

3.1.3 Employee 3.0: Entrepreneurs and Partners

The evolution continued with Employee 3.0; while the introduction of information technology ushered in Industry 3.0 (Oberer & Alptekin, 2018), Employee 3.0 encompassed employees being viewed as entrepreneurs and partners within the organization. This phase was characterized by a more collaborative approach, with employees taking on roles that involved innovation, creativity, and partnership. Employees were expected to contribute to the growth and success of the organization by leveraging their entrepreneurial skills and working closely with their colleagues to achieve common goals (Haijian & Fangfang, 2018).

3.1.4 Employee 4.0: Free-Flowing Viewpoints of Labor

The current phase, Employee 4.0, represents a significant departure from the previous models. Employees are now seen as free-flowing viewpoints of labor, where they can act as individual entrepreneurs within the company. This phase emphasizes the importance of flexibility, adaptability, and continuous learning. Employees are expected to navigate the complexities of the digital era, leveraging advanced technologies and contributing to the organization's innovation and growth. The role of employees has evolved to include a greater focus on personal development, strategic thinking, and the ability to adapt to rapidly changing environments (Haijian & Fangfang, 2018).

In conclusion, the evolution from Employee 1.0 to Employee 4.0 highlights the increasing importance of autonomy, initiative, and collaboration in the modern workplace. As organizations continue to embrace Industry 4.0, employees are expected to take on more dynamic roles, contributing to the strategic goals of the company while continuously adapting to new technologies and challenges.

3.2 Industry 1.0 to 4.0 and the Link to Employee Evolution

The evolution from Industry 1.0 to Industry 4.0 represents a profound transformation not only in technology but also in how leaders interact with and support their employees. During Industry 1.0, innovation was defined by the rise of mechanization, and technology meant mastering new machinery. Leadership was largely functional, requiring awareness of manufacturing techniques, while employees (or “Employee 1.0”) operated as passive subordinates who simply followed instructions (Haijian & Fangfang, 2018; Oberer & Alptekin, 2018). As the second industrial age emerged—Industry 2.0—electricity and early electronics expanded workplace capabilities. Employees began to self-manage and assert more independence, prompting leaders to adopt structured practices like annual performance reviews. This phase marked the birth of “Employee 2.0,” more autonomous yet still manager-guided (Haijian & Fangfang, 2018). The introduction of computing and the internet defined Industry 3.0, wherein employees evolved into entrepreneurial individuals concerned with personal growth and success. Managers in this era often found themselves lagging behind tech-savvy subordinates, shifting their roles from information gatekeepers to motivators and facilitators (Oberer & Alptekin, 2018). With Industry 4.0 came a hyperconnected world powered by the Internet of Things, where both organizations and employees aimed to optimize success collaboratively. “Employee 4.0” embodies a hybrid mindset—career-focused yet invested in team and enterprise goals. Leaders in this age must be emotionally intelligent, technically skilled, and deeply collaborative, emphasizing innovation, cooperation, and cross-hierarchical thinking (Haijian & Fangfang, 2018; Oberer & Alptekin, 2018).

4. Research Methodology – Participant Study

4.1 Introduction

To understand the impact of technology on employee experience within the hospitality industry, this research employs a qualitative approach. The study focuses on gathering in-depth insights from employees through structured interviews, aiming to capture their perceptions, experiences, and feedback on technological advancements in their workplace.

4.2 Research Design and Strategy

Design Overview: A qualitative approach was chosen for this research to allow for a comprehensive exploration of employee experiences and perceptions. In-person interviews were conducted to gather primary data, ensuring confidentiality and anonymity for participants. This method enabled the collection of rich, detailed responses without the constraints of quantitative surveys.

4.3 Data Collection Methods

Primary Data Collection: Primary data was collected through face-to-face interviews with employees from various departments within the hospitality industry. The interviews followed a structured script of pre-determined questions, allowing participants to describe their experiences and perceptions of technology in their own words. This approach minimized interviewer bias and ensured consistency across interviews.

4.4 Interview Questions

The interview questions were designed to explore various aspects of employee experience with technology, including past and future impacts, challenges, and suggestions for improvement. Key questions included:

1. How has technology impacted your experience as an employee, for better or worse?
2. What impact do you think technology will have on your experience in the future, for better or worse?
3. What challenges have you encountered with technology in your role?
4. If you could suggest one or two changes to enhance your overall experience with technology, what would they be?

5. Data Analysis Methods

A thematic analysis was conducted to identify key themes and patterns in the interview responses. The process involved several steps:

1. **Familiarization with the Data**: Reading and re-reading interview transcripts to gain an in-depth understanding of the content.
2. **Generating Initial Codes**: Organizing the data into meaningful codes that capture specific aspects of employee experiences with technology.
3. **Searching for Themes**: Grouping related codes into broader themes that reflect the core issues and insights from the data.
4. **Reviewing Themes**: Refining and consolidating themes to ensure they accurately represent the data.
5. **Defining Themes**: Clearly defining each theme and its significance in the context of the research.
6. **Writing Up**: Presenting the findings in a coherent and structured manner.

6. Results

6.1 Introduction

The results of the thematic analysis revealed several key themes related to employee feedback on technology in the hospitality industry. These themes provide valuable insights into the impact of technology on employee experience, highlighting both positive and negative aspects.

6.2 Key Themes

6.2.1 Efficiency and Productivity

Employees reported that technology has significantly improved efficiency and productivity in their roles. Tools such as time tracking systems, communication platforms, and data management software have streamlined processes and reduced manual tasks.

6.2.2 Challenges and Adaptability

Despite the benefits, employees also highlighted challenges associated with technology. Issues such as system glitches, complexity, and the need for continuous adaptation were common concerns. Employees emphasized the importance of ongoing training and support to navigate these challenges.

6.2.3 Communication and Collaboration

Technology has enhanced communication and collaboration among employees. Tools like internal newsletters, chat-based systems, and email have facilitated information sharing and improved coordination across departments.

6.2.4 Future Impact and Concerns

Looking ahead, employees expressed mixed feelings about the future impact of technology. While some anticipated further improvements in efficiency and guest experience, others were concerned about potential job displacement and the loss of human touch in guest interactions.

Word clouds below depict the differences in sentiment between hospitality and non-hospitality workers for technological future changes. In the hospitality word cloud (right), words emerge relating to jobs, human, guests, people, and robots, while on the non-hospitality side (left), words emerge regarding AI, more, help, teachers, and zoom. These factors create an interesting notic AI takin

Figure 1. Word Cloud - Technological Future Impact - https://simplewordcloud.com

6.2.5 Suggestions for Improvement

Employees provided several suggestions for enhancing their experience with technology. These included investing in user-friendly tools, providing regular training and support, and ensuring a balance between automation and human oversight.

7. Discussion

The findings from this research highlight the dual nature of technology's impact on employee experience in the hospitality industry. While technology has brought about significant improvements in efficiency and communication, it has also introduced challenges that require careful management. Organizations must prioritize ongoing training and support to help employees adapt to technological changes and maximize the benefits of these advancements.

8. Conclusion and Next Steps

This research contributes to the understanding of how technology influences employee experience in the hospitality industry. By capturing employee feedback and identifying key themes, the study provides valuable insights for organizations seeking to optimize their use of technology and enhance employee satisfaction. Future research should continue to explore the evolving relationship between technology and employee experience, considering the rapid pace of technological advancements.

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ADDITIVE MANUFACTURING TECHNIQUES FOR REDUCING FAILURE MODES AND ENHANCING DURABILITY IN AEROSPACE COMPONENTS

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Abstract

Additive Manufacturing (AM) transforms aerospace by enabling complex, resource-efficient designs. This paper explores how AM enhances durability and reduces failure modes like fatigue, stress corrosion cracking, and structural failure. Techniques such as Selective Laser Sintering (SLS), Electron Beam Melting (EBM), and Fused Deposition Modeling (FDM) are examined for their advantages over traditional methods. Challenges like material limitations and cost are discussed, highlighting AM's potential for sustainable aerospace innovation.

Keywords: *Additive Manufacturing, Aerospace Components, Selective Laser Sintering, Electron Beam Melting, Selective Laser Melting.*

1. Introduction

In aerospace engineering, the development of parts that are resistant to harsh conditions, i.e., high temperatures in jet engine parts or high loads on airframe structures, is most important. Manufacturers have depended on such reliable processes as forging, casting, and machining because of their reliability and reproducibility (Gupta et al., 2022). However, as these approaches exist, so too are their problems. They occupy enormous volumes of material, limit design freedom, and the features are costly and time-consuming finishing processes. Aerospace manufacturers have only just started to explore Additive Manufacturing (AM), or 3D printing, as a real possibility. Unlike removing material from parts, AM builds parts by adding layers precisely as digital models specify (DebRoy et al., 2018). Because it employs only the material required, waste is significantly reduced. In addition to material savings, AM also allows designers to create intricate internal geometries or lattice structures that are impossible to manufacture at low cost using traditional methods. Aerospace companies have already begun to experience tangible benefits from AM. For example, turbine blades manufactured using AM with titanium alloys have shown better durability and fatigue resistance than those produced through traditional casting.

Additionally, AM simplifies manufacturing by merging several separate parts into one unified piece. This not only removes weaknesses that normally happen at joints but also reduces assembly procedures, saves time in production, and reduces overall costs. Yet for all these promising results, there are still hurdles to overcome. AM-produced parts have varying mechanical strengths based on print orientation, or material anisotropy, making them hard to reliably employ in critical uses. High manufacturing expenses and inconsistent quality across batches further complicate adoption. Additionally, meeting strict aerospace certification standards demands rigorous testing and robust quality control for AM components (Thijs et al., 2013). However, several powder bed fusion

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techniques, each with distinct mechanisms and materials like the Selective Laser Sintering (SLS), which primarily fuses polymer powders using a laser without fully melting them. Selective Laser Melting (SLM) for instance which is often confused with SLS fully melts metal powders using a laser to produce dense metal parts. By contrast, Electron Beam Melting (EBM) utilizes an electron beam in a vacuum to fuse metal powders, offering low residual stress and enhanced fatigue performance.

This paper closely examines three key AM techniques: Selective Laser Sintering (SLS), Electron Beam Melting (EBM), and Fused Deposition Modeling (FDM), to see how each addresses common aerospace failure modes, including fatigue, corrosion cracking, and structural issues. The goal is to critically evaluate current AM capabilities, highlighting their limitations and proposing practical paths for wider adoption in aerospace manufacturing.

2. Key Additive Manufacturing Techniques in Aerospace

Additive manufacturing (AM) has transformed the design of aircraft with the ability to create complex, lightweight, and highly robust components that are not possible or economically viable to manufacture using traditional techniques. The performance improvement necessitates the choice of an additive manufacturing process since different techniques have some advantages and disadvantages. Three popular AM technologies used in aerospace are SLS, EBM, and FDM.

2.1 Selective Laser Sintering (SLS)

Selective Laser Sintering (SLS) applies a strong laser to sinter polymer powder layers selectively to fabricate functional and high-performance components without support (Gibson et al., 2021). Due to its flexibility to design and being efficient in using material, it finds extensive use in non-structural aircraft components, functional mock-ups, as well as individual cabin interiors. The figure below shows a schematic of the SLS printing process.

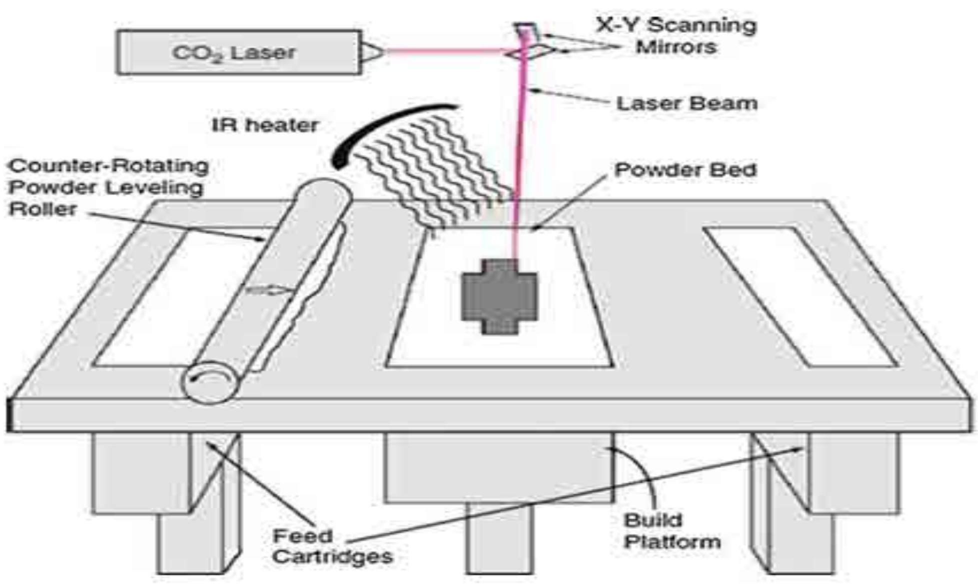

Figure 1. Schematic of the Selective Laser Sintering (SLS) process (Gibson et al., 2021)

Table 1 presents the key advantages, real-world applications, and limitations of SLS within the aerospace sector.

Table 1. Advantages, Applications, and Limitations of SLS in aerospace

Category	**Details**
Advantages	- Enables complex geometries without the need for molds or heavy machining. - Ideal for lattice structures, lightweight ducts, and UAV components. - High material efficiency through powder recycling. - Access to high-performance polymers like PEEK and polyamide composites with thermal and chemical resistance. - Particularly effective for fabricating intricate lattice structures in aerospace applications due to its geometric freedom and precision (Khan & Riccio, 2024).
Applications	- Cabin interior components (ventilation ducts, seat brackets, air distribution elements). - Functional prototyping and rapid design iteration. - UAV structures and satellite housings where weight reduction and thermal stability are key (Thijs et al., 2013). - Useful for both concept development and final part production.
Limitations	- Limited to polymers and thermoplastics, which lack strength for high-stress components. - Surface roughness and porosity may require post-processing (vapor smoothing or polishing). - Additional finishing increases production time and cost, limiting its use for flight-grade components (Thijs et al., 2013).

2.2 Electron Beam Melting (EBM)

EBM is a powder-bed fusion technology that utilizes a high-energy electron beam to melt metal powder in a vacuum and create a dense aerospace component with enhanced mechanical properties (Rafi et al., 2013). It is predominantly utilized for high-strength titanium and nickel-based superalloy components because it has low residual stress and excellent fatigue behavior. The EBM process as seen below shows the cycle involved in generating parts using the EM process.

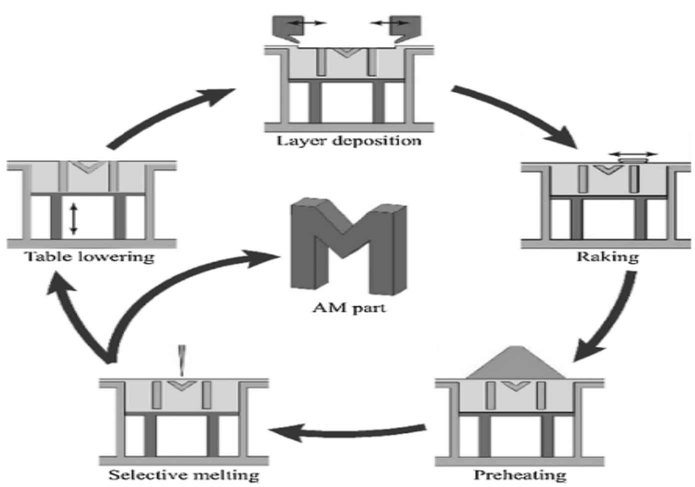

Figure 2. Schematic of EBM Process (Gisario, et al. 2019)

Table 2 outlines the strengths, applications, and challenges of Electron Beam Melting (EBM) in the aerospace manufacturing sector.

Table 2. Advantages, Applications, and Limitations of EBM in Aerospace Applications

Category	Details
Advantages	- High mechanical strength and fatigue resistance, especially in Ti-6Al-4V components. - Superior fatigue endurance makes it suitable for turbine blades and landing gears. - Low residual stress and high material density due to vacuum processing. - Compatible with aerospace-grade metals like titanium, nickel, and cobalt-based superalloys (Khan & Riccio, 2024).
Applications	- Lightweight, heat-resistant turbine blades that boost engine efficiency and longevity. - Titanium EBM-manufactured landing gear brackets reduce weight while maintaining structural integrity. - Nickel-based EBM parts offer oxidation resistance for rocket propulsion systems (Rafi et al., 2013).
Limitations	- Slower build rates and high operational costs. - Less ideal for large-scale/high-volume production compared to SLS or FDM. - Often requires extensive post-processing (e.g., HIP, polishing) to meet aerospace surface quality and performance standards.

2.3 Fused Deposition Modeling (FDM)

FDM is a thermoplastic extrusion-based AM process that fabricates parts layer by layer for functional prototypes and low-load aerospace parts. While it lacks the strength required in flight-critical structures, it has widespread applications in rapid prototyping and non-structural aerospace engineering (Alafaghani et al., 2017).

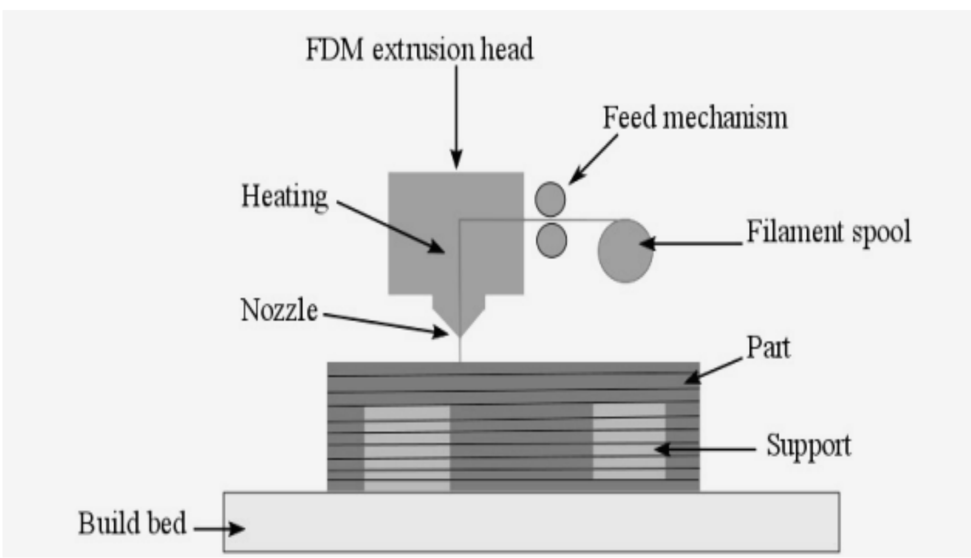

Figure 3. Fused Deposition Model Schematic (Alafaghani et al., 2017)

Table 3 captures the primary advantages, specific aerospace use cases, and notable drawbacks of FDM.

Table 3. Advantages, Applications, and Limitations of FDM in Aerospace Applications

Category	Details
Advantages	- Cost-effective for rapid prototyping with short development times. - Applicable to one-off cabin fixtures and UAV parts. - Results in minimal material waste, which aids sustainable manufacturing (Gupta et al., 2022).
Applications	- Used in functional aerodynamic prototypes and structural testing of parts before full-scale manufacturing. - Used to create cabin components like armrests, seat indicators, and ducting systems with high-performance polymers. - Enables custom-designed light UAV components, specifically CFRP-based, for non-load bearing aerospace parts (Gibson et al., 2021).
Limitations	- Inferior inter-layer bonding that results in anisotropic mechanical properties, which are incompatible with high-load structure elements. - Surface roughness requires additional surface finishing (e.g., sanding, chemical smoothing) to aerospace aerodynamics and quality standards (Alafaghani et al., 2017).

3. Solutions Provided by Additive Manufacturing

The application of AM in aerospace engineering provides innovative solutions to long-standing structural and material challenges. Traditional manufacturing techniques, such as casting and forging, are often material-intensive, geometrically constrained, and prone to defects that contribute to failure modes such as corrosion cracking, structural failure, and fatigue degradation (Gisario et al., 2019). AM enables precise material placement, weight reduction, and tailored microstructures, significantly enhancing the durability and reliability of aerospace components. This section explores the role of AM in mitigating corrosion cracking, reducing structural failure, and enhancing fatigue resistance.

3.1 Mitigating Stress Corrosion Cracking

Corrosion is a critical failure mechanism in aerospace components that are exposed to high humidity, salt, and high temperatures. Traditional alloys like Ti-6Al-4V and nickel-based superalloys are vulnerable to stress corrosion cracking (SCC) and oxidation-related degradation. AM addresses these issues by refining the microstructures of these alloys, reducing porosity, and allowing grain orientation control. Techniques like Selective Laser Melting (SLM) and Electron Beam Melting (EBM) significantly lower residual stress that could occur from manufacturing and improve resistance to SCC (Gupta et al., 2022). EBM-processed Ti-6Al-4V components, for instance, show enhanced corrosion resistance and durability under high-temperature conditions. AM also enables the direct application of corrosion-resistant coatings and produces parts with fewer voids than conventional casting, minimizing crack initiation sites. These benefits are evident in applications like turbine blades and nickel alloy brackets, where improved oxidation resistance and mechanical stability contribute to better performance and longer service life (Gisario et al., 2019).

3.2 Reducing Structural Failure

Structural failure in aerospace components often results from residual stresses, material defects, and geometric limitations introduced by casting, forging, and machining (DebRoy et al., 2018). AM addresses these issues through topology-optimized designs that distribute loads efficiently, reducing stress concentrations and enhancing durability. Unlike traditional joining methods that create fatigue-prone zones, AM produces single, continuous structures with fewer weak points (Gibson et al., 2021). Additionally, AM allows for tailored alloy compositions and localized reinforcement in high-stress regions, improving resistance to crack growth and impact damage. A topology-optimized aircraft pylon (Figure 4) illustrates how AM achieves lightweight, high-strength designs that surpass conventional manufacturing (Zhu et al., 2016).

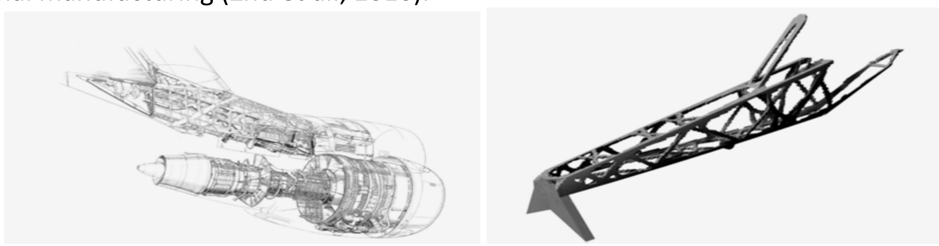

Figure 4. Traditional Manufactured Aircraft Pylon (a) vs AM-optimized Aircraft Pylon (b)

3.3 Enhancing Fatigue Resistance

Aerospace components face fatigue crack growth from constant cyclic loading. Traditional machining introduces surface flaws and microstructural defects that reduce fatigue life. AM improves fatigue performance through precise grain structure control and reduced internal defects (Frazier, 2014). Techniques like Selective Laser Melting (SLM) and Electron Beam Melting (EBM), combined with post-processing such as Hot Isostatic Pressing (HIP), enhance material uniformity and eliminate voids, further extending fatigue life (Zhu et al., 2016).

Powder bed fusion processes optimize parameters like laser power and scanning speed, minimizing porosity and crack initiation. Support structure optimization, shown in Figure 5, further reduces crack formation during the build process (Liu et al., 2018). AM-produced Ti-6Al-4V components demonstrate up to 30% longer fatigue life than cast parts due to improved residual stress profiles and refined microstructures (Rafi et al., 2013).

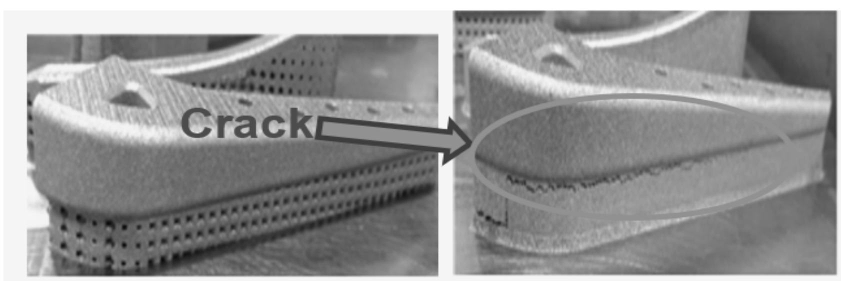

Figure 5. Support structure design optimization for a part made by the laser metal AM process: a.) Part built with a generic, un-optimized support has cracks, and b.) part built with an optimized support structure remains intact. (Liu et al., 2018)

4. Case Studies

The following case studies were selected to highlight diverse aerospace applications of AM processes. GE Aviation, Boeing, and SLM-based turbine blades represent leaders in metal and polymer AM, providing real-world evidence of how AM addresses critical aerospace challenges in fatigue, corrosion resistance, and structural optimization.

4.1 Electron Beam Melting (EBM) Application in Aerospace: GE Aviation Fuel Nozzles

Electron Beam Melting (EBM) has transformed aerospace manufacturing, as demonstrated by GE Aviation’s LEAP engine fuel nozzles. Using EBM, GE consolidated 20 separate parts into a single additively manufactured component, reducing nozzle weight by approximately 25%, a significant advantage for improving aircraft fuel efficiency and reducing emissions (Yusuf et al., 2019). Beyond weight savings, the EBM nozzles exhibited nearly five times greater durability than conventionally manufactured versions, enhancing fatigue resistance during cyclic engine loading (Rafi et al., 2023). This process also simplified the supply chain, reducing assembly steps and production time, while improving overall reliability (GE Additive, 2020). The LEAP nozzle exemplifies how AM optimizes performance and manufacturing efficiency for complex aerospace components.

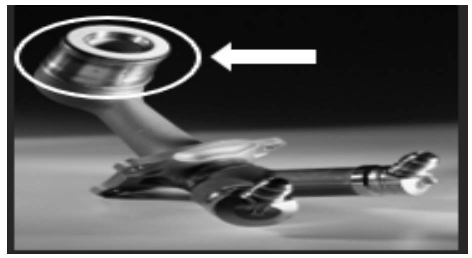

Figure 6. A single 3D-printed Fuel Nozzle (GE Additive, 2020)

4.2 Selective Laser Sintering (SLS) in Aerospace: Boeing’s Air Duct Components

Boeing has effectively adopted SLS for fabricating air ducting components intended for both military and commercial aircraft. Specifically, Boeing utilized flame-retardant nylon material to manufacture these ducts, taking advantage of SLS's ability to create lightweight and complex shapes that are otherwise challenging to achieve through conventional manufacturing methods. Implementing SLS technology allowed Boeing to achieve approximately a 30% weight reduction in these components, significantly enhancing fuel efficiency and aircraft performance. Additionally, adopting SLS resulted in faster prototyping and production cycles, improved component reliability, and decreased complexity during assembly, thereby streamlining overall manufacturing processes. An example of an AM printed air duct component can be seen in figure 7 below. The weight reduction addresses the structural failure concerns in Section 3.2 by optimizing load distribution in non-critical components.

Figure 7: 3D Printed Air Duct Components (3D Printing Industry, 2019)

4.3 Selective Laser Melting (SLM) in Aerospace: Inconel 718 Turbine Blades

Selective Laser Melting (SLM) enables the fabrication of Inconel 718 turbine blades with complex geometries and improved mechanical properties. Periane et al. (2019) found that combining SLM with Hot Isostatic Pressing (HIP) and Aeronautic Heat Treatment (AHT) increased hardness by 31% and improved fatigue resistance, with dry-machined parts reaching endurance limits up to 1040 MPa. Lesyk et al. (2022) further showed that HIP treatment reduced porosity from 99.862% to 99.997% and refined pore sizes, producing isotropic equiaxed grains. These enhancements improved fatigue life and corrosion resistance, addressing the failure modes discussed in Sections 3.1 and 3.3. Together, these studies demonstrate that SLM, when paired with post-processing, produces aerospace-grade turbine blades with superior durability and weight reduction benefits.

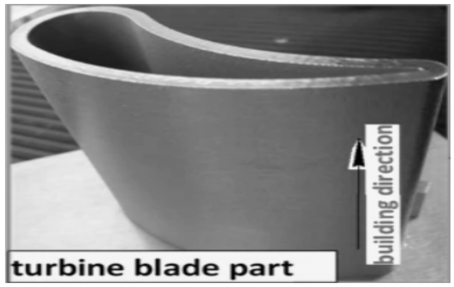

Figure 8: 3D SLM-fabricated turbine blade (Lesyk et al., 2022)

Collectively, these case studies reveal that while AM enables unprecedented part integration and weight reduction, performance consistency and cost remain significant challenges. Hybrid strategies, surface refinement techniques, and rigorous post-processing remain essential to meet aerospace standards.

5. Challenges in Additive Manufacturing for Aerospace Response Variables

While AM has revolutionized aerospace engineering by facilitating the creation of lightweight, high-strength, and customized components, there are still some fundamental challenges. Such challenges include material limitations, process inhomogeneities, and manufacturing costs, which impact structural integrity, reliability, and economic feasibility. Certification processes are lengthy and costly. While GE's fuel nozzles passed rigorous FAA standards, smaller companies often struggle to meet such requirements without external partnerships. Minimising such challenges is critical to facilitating the mass adoption of AM technologies in aerospace applications.

5.1 Material Limitations

Many aerospace materials face challenges in AM due to thermal distortion, poor microstructural uniformity, and difficult printability. While titanium alloys (Ti-6Al-4V), Inconel 718, and some aluminum alloys are widely used, high-strength steels, advanced composites, and certain heat-resistant alloys remain difficult to process with powder bed fusion and extrusion methods. AM parts also exhibit anisotropic mechanical properties, residual stresses, and porosity, reducing fatigue life in critical aerospace structures (Rafi et al., 2013). For instance, SLM-produced Inconel 718 turbine blades suffer from grain growth and phase transformations at high temperatures (Gisario et al., 2019). Ongoing research focuses on developing high-entropy alloys (HEAs) and ceramic matrix composites (CMCs) for AM, while post-processing methods like heat treatment and Hot Isostatic Pressing (HIP) improve mechanical performance and fatigue resistance.

5.2 Process Stability Challenges

Maintaining process repeatability and reliability in AM remains a key challenge for aerospace applications. Unlike traditional machining, AM processes show variability in melt pool behavior, layer adhesion, and cooling rates, leading to defects like incomplete fusion, cracks, and porosity that compromise part integrity (Gupta et al., 2022). Thermal warping from residual stresses and temperature gradients further impacts dimensional accuracy, especially in large aerospace components (Gibson et al., 2021). The lack of real-time defect monitoring forces reliance on extensive post-production testing. Large AM structures, such as aircraft frames, often require additional machining to meet tight tolerances due to thermal distortion (Goh et al., 2017).

5.3 High Production Costs

Despite its advantages, AM in aerospace faces high production costs driven by expensive raw materials, slow build rates, and costly post-processing (Gisario et al., 2019). Aerospace-grade metal powders used in AM can cost five to ten times more than conventional materials (Gibson et al., 2021). Powder bed fusion methods like SLS and EBM have long production times and require extensive post-processing, adding 30–50% to total costs. These challenges limit AM's economic feasibility for large structures like aircraft frames and turbine blades, where traditional casting remains cheaper. Table 4 highlights the stark cost difference between Selective Laser Sintering and High-Pressure Die Casting (Atzeni & Salmi, 2012).

Ongoing research in hybrid manufacturing and metal powder recycling aims to reduce material and processing costs, making AM more competitive for aerospace applications.

Table 4. Cost Comparing between Traditional Manufactured and SLS Parts. (Atzeni and Salmi 2012)

	High-Pressure Die-Cast Part ($)	**Selective Laser Sintering Part ($)**
Material cost per part	2.82	28.13
Pre-processing cost per part	-	8.72
Processing cost per part*	0.28 + 22,890/N	514.03
Post-processing cost per part	19.51	21.80
Assembly	0.59	-
Total	**23.19 + 22,890/N**	**573.68**

5.4 Economic and Certification Challenges

Additive manufacturing (AM) in aerospace faces economic and certification hurdles despite successes like GE Aviation’s FAA-certified LEAP nozzles, smaller aerospace firms struggle with the high costs and technical demands of AM certification (GE Additive, 2020). Certification remains lengthy due to the need to prove process consistency and material reliability across varying feedstock, build parameters, and part orientations (FAA, 2024). To streamline approvals, ASTM International’s Committee F42 develops standards like ASTM F3303 for powder bed fusion qualification, while joint FAA-EASA workshops promote international alignment (EASA, 2025). However, the high cost of qualification and evolving regulatory frameworks still limit widespread AM adoption in aerospace.

5.5 Scalability and Certification Limitations

Scaling additive manufacturing (AM) for large aerospace components introduces critical challenges in maintaining part quality and consistency. Studies on Airbus’s SLM-produced brackets highlight recurring issues like porosity, residual stress, and thermal distortion, which hinder certification efforts (Wang et al., 2024). These defects compromise fatigue life and structural integrity, reinforcing the concerns discussed in Section 3.2. Certification processes demand strict repeatability and flaw-free builds, yet large-scale AM struggles with process variability and thermal management. While evolving ASTM and FAA standards aim to streamline qualification, the costs and technical hurdles limit adoption. Addressing scalability requires advanced process control, in-situ monitoring, and optimized post-processing to ensure aerospace-grade reliability.

6. Conclusion

Selective Laser Sintering (SLS), Electron Beam Melting (EBM), and Fused Deposition Modeling (FDM) provide unique strengths for aerospace manufacturing. SLS enables lightweight polymer parts for non-structural uses, EBM produces high-strength titanium and nickel alloy components, and FDM supports rapid prototyping and interior components. However, broader adoption faces challenges such as material anisotropy, residual stresses, and surface roughness, which compromise mechanical integrity. Additionally, high material costs, slow production rates, and post-processing burdens impact economic viability. Innovations in hybrid manufacturing, powder recycling, and AI-based quality control are addressing these barriers. Future efforts should focus on aerospace-specific materials like high-entropy alloys (HEAs) and ceramic matrix composites (CMCs), along with improved process stability and real-time defect monitoring. Post-processing advances, including hot isostatic pressing (HIP) and laser peening, will further enhance fatigue life and reliability. As these innovations mature, AM will play a critical role in producing lighter, stronger, and more reliable aerospace components.

7. Disclaimer Statements

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Conflict of Interest: None

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INCORPORATING COLLABORATION, COMMUNICATION AND CHARACTER INTO ENGINEERING EDUCATION

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Abstract

The goal of KEEN's Entrepreneurial Mindset (EM) framework is to incorporate learning that enhances students' curiosity, connectedness of material, and creates value, which are expressed through collaboration, communication and character. The purpose of this paper is to describe KEEN's Entrepreneurial Mindset, and demonstrate how to enact collaboration, communication and character within engineering courses. The methodology applied was to incorporate active learning within the classroom to encourage collaboration and enable students to become better communicators through Lean Six Sigma projects. Character was incorporated into an engineering economics course ethics materials, with real-world case studies related to ethics and values. Student-based assessments related to collaboration were implemented. Instructor-based assessments were implemented to assess the students' communication skills within Lean Six Sigma project reports. Student-based pre and post ethics tests from the National Professional Engineers Society (NPES) were used to assess the students' skills related to applying a professional code of conduct to real-world examples. Forty-one (41%) of the students had observed racial discrimination, 25% had observed gender discrimination and 20% had not observed any types of ethical dilemmas related to diversity and/or discrimination in their lives. The ethics module improved ethics learning related to identifying potential ethics violations by 17.9%, with a pretest average score of 3.0386 out of 5, compared to an improved average score post intervention of 3.5818, with a p-value on a paired t-test of ~0.000. The results were positive and demonstrated the application of EM related to collaboration, communication and character within engineering courses.

Keywords: *Engineering Education, Ethics, Character, Collaboration, Communication, Entrepreneurial Mindset*

1. Introduction

KEEN is a partnership of more than sixty colleges and universities in the United States with the mission: "To reach all undergraduate engineering students with an entrepreneurial mindset (EM) so they can create personal, economic, and societal value through a lifetime of meaningful work." (EngineeringUnleashed.com) An entrepreneurial mindset is a way of thinking that incorporates a problem solving focus, along with the 3C's, curiosity, connectedness and creating value to enhance the skills related to an additional 3 Cs of collaboration, communication and character. Curiosity encourages the students to become curious in their approach to solving problems, learning and applying engineering skills and challenging the status quo and the way that problems are typically solved. Connectedness is a mindset where students connect the material within and across their engineering courses and disciplines and are able to see the big picture of the problem to be solved. Creating value is a focus on the customers' needs of the engineering products and services that are designed or improved and keeps an eye on the ultimate goal to be achieved. Collaboration

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incorporates students working together in the classroom, so that they learn effective teamwork skills that they'll need in the work environment. Most, if not all engineering disciplines require engineers across these disciplines to work together to design and deploy effective products, processes and services. Excellent teamwork requires team members to be able to encourage engagement, motivation and participation within the team to achieve the team's goals, reduce conflict and create innovative solutions. Communication skills are critical for engineers to be able to explain their solutions, and interact with customers to understand and elicit their needs. Character incorporates values and the understanding of how to deal with ethical dilemmas in the workplace and in life, especially with respect to the decisions that engineers must make as they design and deploy products, processes and services, related to society, employees, the environment, to name just a few of the multi-factors that engineers impact.

EM brings a different mindset to the engineering skillset that is taught in engineering programs. The purpose of this paper is to describe KEEN's Entrepreneurial Mindset, with respect to the 6 C's, and demonstrate how to apply collaboration, communication and character within engineering courses. The paper will connect to the literature related to the entrepreneurial mindset and the 6 Cs, describe the methodology applied within the classroom, discuss the critical results, conclusions and future work (No author, 2025).

2. Literature Review

2.1 Entrepreneurial Mindset Framework

A study by Ritz et. al (2025) found that faculty members at the studied institution who successfully were able to adopt the Entrepreneurial Mindset (EM) of the KEEN framework did so by applying professional development offerings of the Designing for Sustained Adoption Instrument (DSAAI) guidelines to sustain the adoption. Active learning is frequently applied within the EM framework as a mechanism to apply the 3 Cs of Curiosity, Connectedness and Creating Value. Tembrevilla et al. (2023) found that experiential learning has been successfully carried out via diverse methodologies, but that there is a strong need to enrich it with a theoretical basis. Grossnickle (2016) provided a definition of curiosity as, "the desire for new knowledge, information, experiences, or stimulation to resolve gaps or experience the unknown" (p. 26).

2.2 Character and Engineering Ethics Education

Several recent studies are illustrating that engineering educators need to apply new approaches to teaching engineering ethics. As Artificial Intelligence (AI) and other advanced technologies are becoming more prevalent, the teaching of engineering ethics, must also evolve with these advancing technologies. In a study on engineering education (Pierrakos, et al., 2019), the authors found that there were several suboptimal characteristics in how engineering ethics is taught. They found that the engineering ethics education was not clearly linked to the ethical theories that would help with ethical reasoning and making better decisions. The ethics in engineering education focuses heavily on compliance or rule-based ethics, providing less ability to internalize moral values and virtues. Many of the ethics case studies included rare or extreme circumstances, such as the NASA space shuttle Challenger disaster. These case studies convey the notion that this type of reasoning is infrequent and not common. These authors suggest incorporating character education as an approach to teaching engineering ethics.

Another study proposed that insights and methods from moral and cultural psychology could be used to improve engineering ethics education and assessment (Clancy et al., 2025). A study by Dikici (2021), discusses the need to make ethics sustainable, and what needs to be done to raise engineering ethical standards and how engineering ethics education is presented to engineering faculty. Clancy et al. (2022) discuss how global engineering ethics should be taught using case studies incorporating a cross-cultural and/or international dimension.

The literature highlights the need for enhancing how engineering educators are teaching engineering ethics to their students.

3. Methodology

Real-world experiential learning opportunities were incorporated into a Lean Six Sigma course within an Engineering Technology undergraduate program to enhance collaboration and teamwork, as well as communication. Collaboration and teamwork were assessed through student-based surveys where each team assessed each other and themselves related to how they worked together as a team, as well as reflecting on the quality and quantity of the deliverables for the project. The communication skills assessment were instructor-based upon the ability of the students to communicate the deliverables of their Lean Six Sigma project, through a written report and an oral presentation after the DMAIC (Define-Measure-Analyze-Improve-Control) phases of the project. Grading rubrics were developed by the instructor that were provided to the students at the beginning of the semester.

Character competencies related to engineering ethics materials were provided to the students as a module in an Engineering Economic Analysis course. This course is taken by sophomores through juniors across a wide variety of engineering disciplines within a College of Engineering. Lecture materials on engineering ethics along with active learning exercises were incorporated into the classroom setting.

3.1 Collaboration and Communication

Collaboration and communication were incorporated into a Lean Six Sigma course where the students work on a Lean Six Sigma project on teams. The purpose of the Lean Six Sigma project was to provide an experiential learning opportunity to the students throughout the semester. The DMAIC problem solving approach was to be applied to a “real world” project to help synthesize the course content. The structure of the project was that the students worked together on their project throughout the semester. The lecture materials provided the tools and methodology that the students applied on their project. Grading rubrics for each phase of the DMAIC methodology showed the tools that were to be applied during the phase. A screen shot of the first page of the Define phase grading rubric is shown in Table 1:

Table 1: Lean Six Sigma Project Grading Rubric for the Define Phase

Criteria	Grading Rubric for Define Phase	Points Available	Points Given	Comments
Quality of report content and grammar	10 Concise, description of each tool, describe key findings regarding tool, well written and organized. 6 – 9 Doesn’t thoroughly discuss the topic, missing key findings, and/or poorly written 2 - 5 Poorly written, lacking detail, missing description of tool and/or findings 0 – 1 Missing or superficial	10		

Criteria	Grading Rubric for Define Phase	Points Available	Points Given	Comments
Project Charter (problem overview, problem statement, goals, scope)	10 Well defined problem overview, statement, goals and scope. Problem statement describes the problem while being specific, describing the magnitude of the problem quantitatively, and with time-based measure. Goals are SMART (Specific, Measurable, Attainable, Realistic and Time-based). Scope is reasonable for the semester project timeframe, describing what is in scope from a process perspective and what is not included in the scope. 6-9 Less thorough description of the problem, not very specific, no or little description of the magnitude of the problem without a time-based measure. Goals are not SMART. Scope is too large or too small. 0-5 Lacks detailed description of the problem overview, statement, goals and scope	10		
Critical to Satisfaction (CTS)	10 Sound description of the Critical to Satisfaction, capturing what is critical to satisfaction, quality, delivery/timeliness, cost, process or safety. Focused on the output or outcomes. 6-9 Inadequate description of the CTS, don't align to satisfaction, quality, delivery/timeliness, cost, process or safety. Not focused on output or outcomes. 0-5 Missing or very poor CTS.	10		
Stakeholder analysis	10 Thorough descriptions of the customers/stakeholder groups involved in the project. Define as primary stakeholders (touch or own the process) or secondary (have a stake, but do not own the process). Clear description of the impacts and concerns of the stakeholder group. Reasonable identification of where the stakeholders are at the beginning of the project from a receptivity to the project, and where they need to be in the future to implement improvements. All appropriate stakeholders are identified that are impacted by the process and project. 6-9 Unclear stakeholder definition/description. Missing type, impact/concern, receptivity, and/or key stakeholder groups. 0-5 Missing or very poor description of the stakeholder elements.	10		
Stakeholder receptivity communication plan	10 Includes audience, objectives of communication, the key message, the media, who owns the communication, and the frequency for communicating the Lean Six Sigma project. 6-9 Missing some of the communication fields, or poor description 0-5 Missing and /or very poor description of fields in communication plan	10		

Criteria	Grading Rubric for Define Phase	Points Available	Points Given	Comments
Stakeholder receptivity change plan	10 Developed clear and specific actions for how to move stakeholders to be more receptive to the planned process change. Includes Stakeholders, desired behaviors, actions, and progress of achieving desired behaviors. 6-9 Needs better description of fields, and/or missing some fields 0-5 Missing some fields and/or unclear description	10		
Project Risk analysis	5 Well defined project risks that could impact ability to successfully complete the project. Clear and concise description of risks, and risk mitigation strategy, identify reasonable impact and probability of occurrence of risk events. 3-4 Needs better description of fields, and/or some missing. 0-2 Missing some fields and/or unclear description.	5		
SIPOC	10 Includes 5 to 7 high level process steps in the process to be improved. Aligns to scope of the project. Includes process steps as verb-noun names. Suppliers and Customers are stakeholder groups (nouns), align with stakeholders in the stakeholder analysis. Inputs and outputs are information, materials, supplies, documents, etc used within the process steps (nouns). 6-9 Needs better description of fields, and/or missing some fields. Lacking verb-noun names in process steps, and/or nouns in other fields. Not aligned to stakeholder analysis and scope of project and process to be improved. 0-5 Missing some fields and/or unclear description, and/or lacks alignment with project scope and stakeholder analysis.	10		
Potential benefits	5 Well defined potential project benefits, including financial, quality, customer benefits of the project. Well aligned to CTS. 3-4 Poor definition of potential project benefits, not align to CTS. 0-2 Missing or poor potential project benefits.	5		
Project plan	5 Well defined project plan, with reasonable activities, resources and timelines. 3-4 Needs better list of activities, with more reasonable timelines. 0-2 Missing some fields and/or unreasonable timelines.	5		
Rules of Engagement	5 Well defined rules of engagement for the team. Helps team to understand team members' expectations, and build trust within the team. 3-4 Non-original rules of engagement, not created specific to the team, doesn't build trust within the team. 0-2 Missing or poor rules of engagement.	5		

Criteria	Grading Rubric for Define Phase	Points Available	Points Given	Comments
PowerPoint presentation	10 PowerPoint represents an executive summary, 10 to 12 slides. Includes graphics, limited text and bulleted text. Clear, concise, well organized, flows well, and excellent grammar. Conveys key analysis, results and conclusions from the phase. Team presents well, and responds to questions effectively. 6-9 Not clear, concise, or well organized. Some grammatical errors. Team does not respond to questions well. Doesn't convey phase results well. 0-5 Poor presentation, doesn't flow well at all, grammatical errors, poor use of and/or presentation of the tools within the phase. Conclusions are not logical or are missing. Description of the tools is lacking.	10		
TOTAL		100		

3.2 Character Based Engineering Ethics

The instructor provided a lecture on engineering ethics, based on a chapter in the Engineering Economic Analysis book (Furterer & Meckstroth, 2025), which included the following topics:

- Importance of ethics,
- Professional engineers code of ethics,
- Big picture issues
    - Political morality questions concerning technology, equality, freedom in society, professional ethics
    - Institutional design issues
    - Toxic workplaces, bullying and discrimination, and case studies on ethics.

The learning objectives included:

- To understand the importance of ethics in engineering practices and environments
- To be able to identify the ethical issues within engineering practices
- To be able to discern the appropriate ways to deal with ethical dilemmas

The students reviewed two case studies, one concerning technology, the other regarding toxic workplaces and bullying. The technology related engineering case study that was part of the lecture and the homework assignment, was the Boeing Case Study 737 Max Ethical Dilemma (Furterer & Meckstroth, 2025).

The following key points, along with a Wallstreet Journal video was reviewed (Furterer & Meckstroth, 2025)

- *"The Boeing 737 Max aircraft was as the Wall Street Journal investigation said, "a relatively small design issue that exploded into massive catastrophe" (WSJ, 2020).*
- *The brand-new plane crashed twice within five months causing the loss of 346 lives. Boeing had been the "gold standard of engineering excellence", but due to these engineering and ethical failures, the survival of their company may be at risk.*
- *When the re-designed Max first came out, Boeing couldn't produce them fast enough. They were making record-breaking revenue and profits.*
- *On October 29, 2018, the first of the two 737 Max airplanes crashed. The first was operated by Lion Air, crashed into the Java Sea within minutes of take-off, killing everyone on board. The second crash occurred on March 10, 2019, in Ethiopia, killing all 157 people on board.*

China was the first country to ground the 737 Max before the Federal Aviation Administration (FAA) grounded it two days later."

The toxic workplaces and bullying case study included the situation where a female faculty member in an engineering department at a private university, went through an extremely toxic work environment, and was bullied by colleagues within the department. Following is the ethics case study on a toxic and bullying workplace from Furterer & Meckstroth, 2025.

Some of the elements that were addressed in the case study included:

- Described how engineering departments can be extremely toxic for women and minorities.
- Provided an example of a toxic work environment for a department chair that had recently been promoted, due to bullying by colleagues, and lack of support by administration.
- Provided details of how the chair was treated unfairly, by abruptly being removed for her leadership position, without an opportunity for an improvement plan, due process, or detailed feedback related to perceived issues.
- Details of how the chair was contracted to teach summer classes, but was removed from them, and not paid what she was owed.

The following questions were discussed within student teams and with the entire class (Furterer & Meckstroth, 2025).

1) *"What role did the university administration (President, Provost, Associate Provost, Dean (Interim)) have in enabling the toxic work environment?*
2) *What could the university administration have done to eliminate the toxic work environment?*
3) *What could the Department Chair's colleagues have done to support her within the toxic work environment?*
4) *Should the Department Chair have stayed at the University as she had tenure within the university, as her new position that she took after she left was non-tenured?*
5) *What could the Department Chair have done differently to handle the bullying and toxic work environment?*
6) *What would you do if this situation happened to you if you were the Department Chair, one of her colleagues or even the bully?"*

A homework and an exam question were given to the students where they reviewed different ethical scenarios with potential violations of the professional engineers code of conduct and had to identify which canons of the National Professional Engineers Society (NPES) code of ethics were violated.

Part of the homework question is shown in Table 2.

Table 2: Ethical Scenarios Sample to Identify Potential NSPE Code of Ethics Violations

Potential Violations	1. Engineers shall hold paramount the safety, health, and welfare of the public.	2. Engineers shall perform services only in the areas of their competence.	3. Engineers shall issue public statements only in an objective and truthful manner.	4. Engineers shall act for each employer or client as faithful agents or trustees.	5. Engineers shall avoid deceptive acts.
a) A new engineer has been hired as a consultant. She was fired from a previous job for inappropriately sharing client confidential data. Part of her responsibilities for her new job are to access client confidential data. She did not notify the consulting company, but this was identified by the press.	X				X

4. Results

4.1 Collaboration

Collaboration was assessed through student peer review of their teamwork, as shown in Figure 3. The teamwork amongst team members improved as they moved through the DMAIC phases from 73% to 100% teamwork scores. Each team member rated themselves and each other using a rubric that assessed contribution during team meetings, individual contribution outside of meetings, fostering team climate, on a scale of 1 to 4 with narrative describing each number. The team members then rated each team member, including themselves, with the following instructions: "Assign a point value that equates to the effort and quality of the team members' participation on the team. Each team will assign a total points equal to 100 times the number of team members, across all of the team members. For example if you have 4 team members, you assign across the team members 400 points. If each team member had an equal effort and quality of participation, each person would be assigned 100 points each. If one team member participated at only 80% effort and quality, they would receive 80 points, another team member who did more of the work, might receive 110, another team member might receive 110, and the last team member might receive 100, for a total of 400 points across the team members. Note: you should also evaluate yourself!" Figure 1 shows the average across all teams for this rating on a scale of zero to 100% for each phase.

4.2 Communication

A written report describing the tools applied for the DMAIC phases was required summarizing each phase of the DMAIC method (Define, Measure, Analyze, Improve, & Control). A PowerPoint presentation was prepared and presented by the students summarizing the Define, Measure, Analyze, Improve and Control phase reports. The instructor assessed the reports and presentations for each phase. The results are shown in Figure 2. Communication average scores by DMAIC phases ranged from 90.3% to 96% communication (writing and presentations).

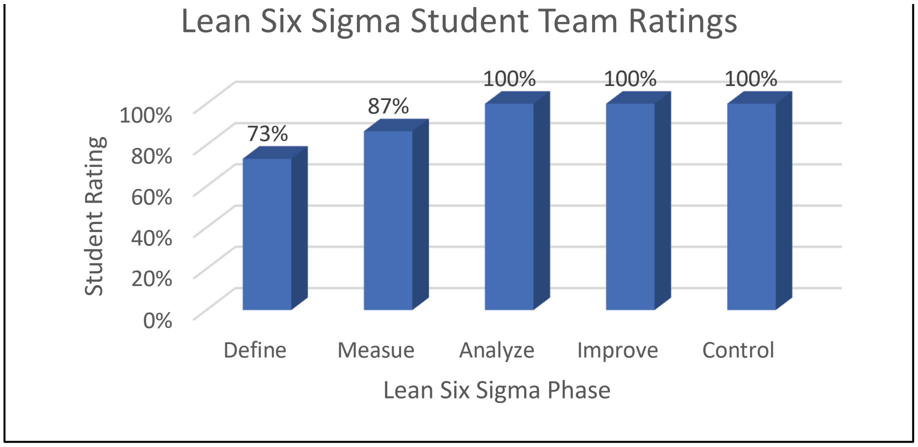


Figure 1: Teamwork Assessment by DMAIC Phase

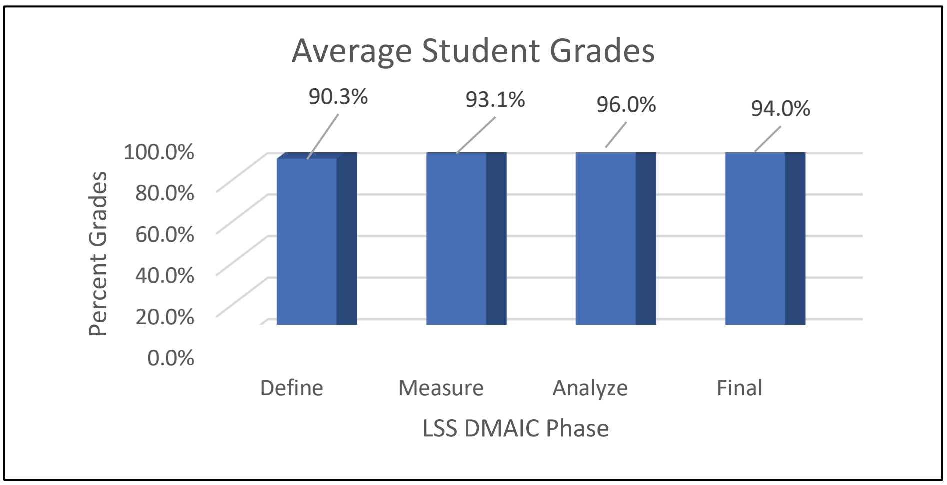


Figure 2: Instructor Assessment of Lean Six Sigma Project Reports and Presentations

4.3 Character - Engineering Ethics

To assess the students' learning of engineering ethics, the students took a pre and post test on ethical scenarios. This was a True and False quiz describing a scenario, where the student was to assess whether the scenario was True or False related to the National Society of Professional Engineers (NSPE) code of ethics. The pretest was taken prior to the lecture on engineering ethics. The post-test was taken after the lecture, active learning and homework problems were completed on the chapter. The pre-test was opened on April 14th, and due on April 16th. The engineering ethics lecture was presented on April 17th, and the post-test was due on April 25th. This resulted in a fairly short window of 11 days; however the scenarios were complex enough that it was difficult to remember the correct answers. The pre-and post-test is provided by NSPE for engineers to assess their knowledge of the code of ethics, by providing ethical challenges and have the participants select which elements of the code are violated.

A paired t-test was performed, using each students' pre and post test scores. There was a statistically significant difference between the average score across the 25 questions with a p-value of ~0.000. The null hypothesis of equal means was rejected, and it was concluded that the students test scores improved after the lecture materials, active learnings and homework on engineering ethics. There was an average of a pretest score of 3.0386, compared to an improved average score post intervention of 3.5818. Ethics violation identification learning increased by an average 17.9% after the engineering ethics module was provided. The statistical tests and histogram of differences is shown in Figure 3.

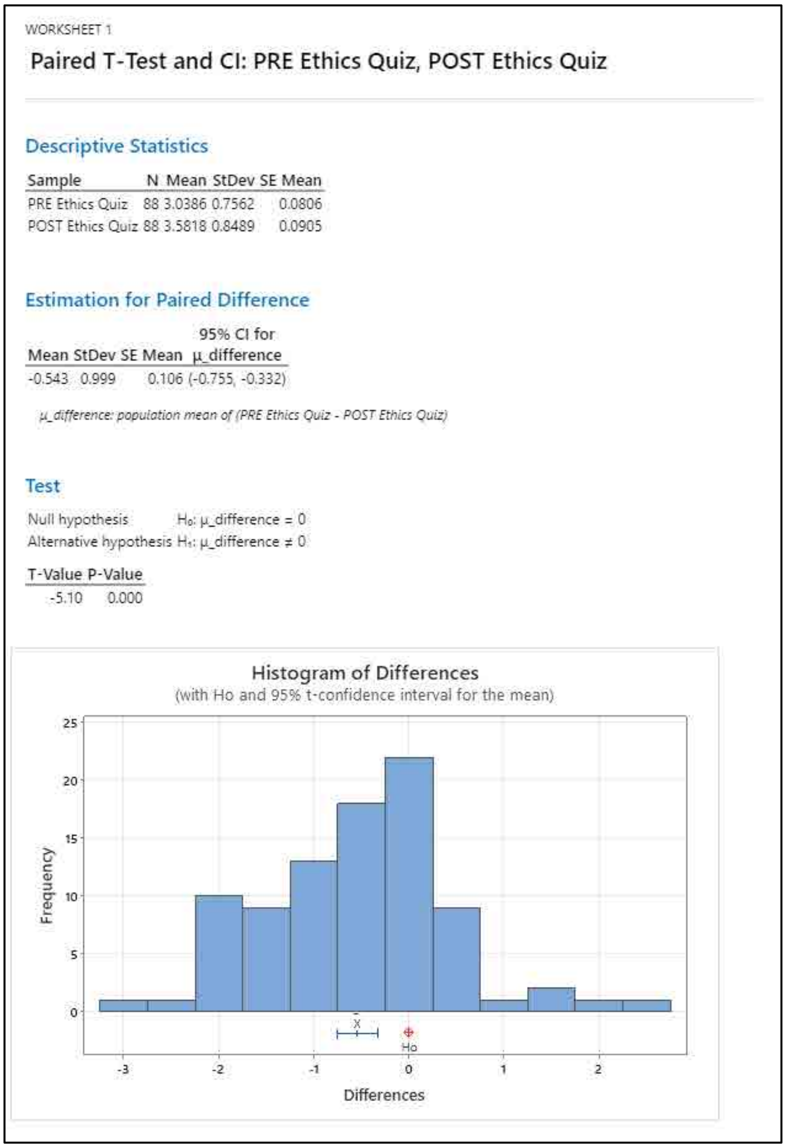
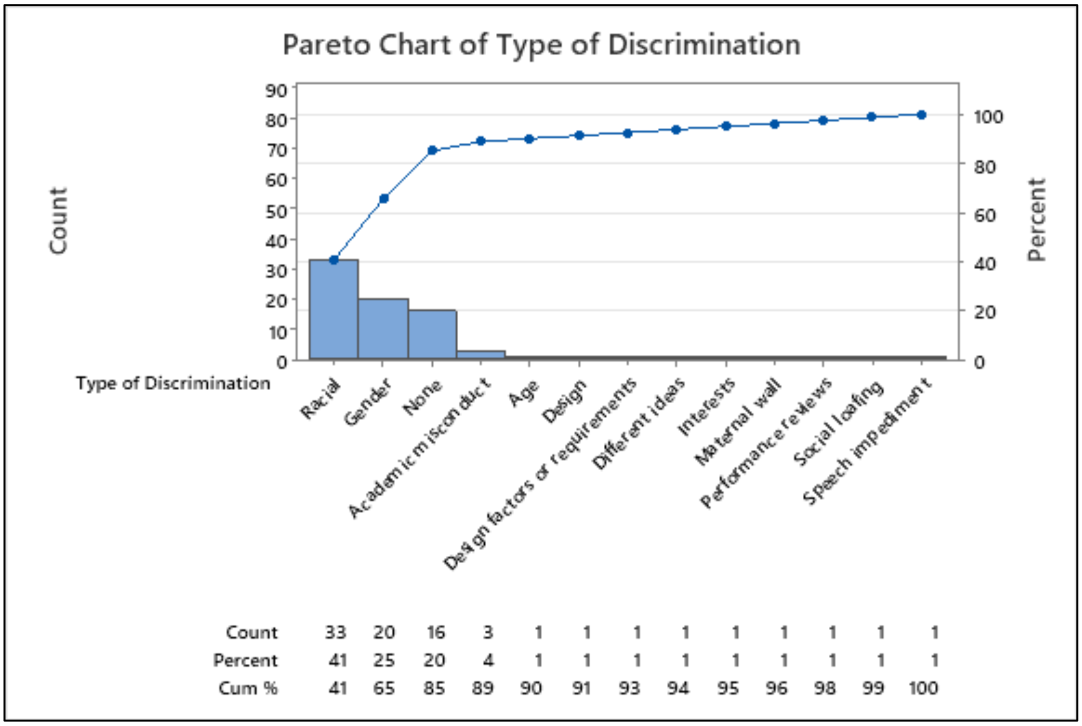


Figure 3: Pre and Post Test Scores

As part of a homework assignment, the instructor asked the students "Have you experienced ethical dilemmas related to diversity and /or discrimination in an engineering or non-engineering environment? Discuss with your team how you handled it, or could handle it better." Out of eighty-one students that responded (74% response rate) to the question, 33 or 41% had observed racial discrimination, 20 or 25% had observed gender discrimination and 16 or 20% had not observed any types of ethical dilemmas related to diversity and/or discrimination. The racial discrimination included students that didn't speak English as their first language had difficulty having their ideas heard on the team, being assigned more work in the workplace, being racially profiled in stores or at theme parks. The most common comment was that the ideas of people of other races on engineering teams were often ignored, especially when English was not their first language. The gender discrimination included not listening to a female engineering students' ideas on a team. A Pareto chart of the results is shown in Figure 4.

Figure 4: Types of Discrimination Observed by Students



5. Conclusions and Future Work

The Entrepreneurial Mindset applied to Engineering Education is a powerful framework. This article demonstrates how collaboration, communication and character can be incorporated through experiential and active learning into the engineering classroom. The Lean Six Sigma experiential projects helped to enhance collaboration and teamwork, as well as the students' communication skills. Incorporating character and engineering ethics through ethics case studies, active learning, and the engineering code of ethics all helped to enhance the skills of the students to identify potential ethics violations, to understand the importance of ethics and to be able to discern appropriate ways to deal with ethical dilemmas. Incorporating human-related ethics of work design, teamwork, bias and how colleagues treat each other in the workplace extend the big ethical issues that our students already face and will continue to in the future. Future research can enhance the active learning and ethical scenarios, incorporating additional scenarios which incorporate the human elements of engineering ethics. Additional assessment methods can also further assess the students' skills related to identifying and dealing with ethical dilemmas, as well as their effectiveness in collaboration and communication. The College is also working to incorporate common language related to EM, and character education in engineering ethics in other courses within the College.

6. Disclaimer Statements

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Conflict of Interest: None

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CLOUDY VIEWS: COLLEGIATE FLIGHT STUDENTS' EMPLOYABILITY RATING OF CFI APPLICANTS BY EXPERIENCE AND GENDER

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Abstract

This research investigated factors that may influence perceived employability of pilots for a certified flight instructor (CFI) position to determine ways to improve workforce diversity within the aviation industry. The experimental study asked a sample of students (306 males and 91 females) at a Part 141 collegiate flight program in Florida to rate CFI applicants on two items: their certainty of hiring the applicant and certainty to have the applicant as a personal CFI. When presented with four professional bibliographies with different gender and flight experience combinations, these items were used to rate employability of an applicant. In line with the understanding that total flight time is a measure of pilot experience and thus qualification, participants had more confidence in the applicants with 1000 hours compared to the applicants with 300 hours. On the other hand, there was no disparity between the scenarios with different gender applicants. This indicates that current students prioritized important hiring variables (i.e., experience in the form of flight time) over gender when evaluating pilot applicants for CFI positions. This is a promising finding for the future of diversity within the aviation industry.

Keywords: *Pilot Hiring, Employability, Certified Flight Instructor, CFI, Gender, Flight Time, Pilot Experience*

1. Introduction

Annual statistics gathered by the Federal Aviation Administration (FAA, 2024), known as the Active Civil Airmen Statistics, reveal that 10% of the total number of pilots (82,817 out of 806,940 pilots as of December 31, 2023) are female. The aviation industry continues to grapple with a pervasive male-dominated culture. While efforts are being made to improve the standing of women in aviation, it has been difficult to find exact barriers to women of qualified experience entering the workforce. The research conducted here determined if biases based on gender and experience exist as early as Part 141 collegiate flight programs.

The purpose of this study was to determine if there is a difference in the employability of pilots for a Certified Flight Instructor (CFI) position by four different hiring scenarios. These hiring scenarios were defined as:

a) High flight experience male (HM): 1000 hours of flight time and he/him pronouns.

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b) High flight experience female (HF): 1000 hours of flight time with she/her pronouns.

c) Low flight experience male (LM): 300 hours of flight time with he/him pronouns.

d) Low flight experience female (LF): 300 hours of flight time with she/her pronouns.

A questionnaire presented these CFI hiring scenarios in the form of four, brief, professional bibliographies. Participants rated two randomly selected bibliographies on two hiring items originally created by Bosak and Sczesny (2011) which, when averaged, determined employability for each hiring scenario. The research question for the study was, is there a difference in the perceived employability of pilots when presented with brief bibliographies for a CFI position of different gender and experience levels? A significant difference in ratings by hiring scenario was expected.

This study provided valuable data for determining perceived gender bias within Part 141 collegiate flight schools when evaluating CFI applicants. Findings indicate how students perceive the qualifications of applicants and the resulting biases that could exist when evaluating male and female pilots at various stages of their careers. The information may be used to develop more inclusive hiring practices in the aviation industry, particularly within flight schools and training programs. Overall, this research promotes understanding of hiring preferences that can create a more diverse and capable pilot workforce in compliance with Title VII of the Civil Rights Act of 1964 (Title VII), which prohibits employment discrimination by sex (EEOC, 1964). As a result, broader implications for aviation recruitment and workforce diversity can inform future training and policy decisions to increase female representation in aviation.

The results are generalizable to students enrolled in collegiate flight programs, particularly those in Part 141 flight schools. The sample is a representative cross-section of this population in terms of training, age, and experience levels. Due to the highly standardized nature of Part 141 programs, these programs maintain consistent training methods and requirements across institutions and should have similar male-to-female student ratios and would, therefore, produce similar results.

2. Literature review

The diversity of the aviation industry is a multifaceted issue that deals with bias and perceptions The following literature review discusses causes of personal bias, perceptions of employability, definitions of flight experience, and how biases impact aviation. Emphasis was placed on the implications of the lack of diversity within the aviation industry to show the importance of research into this topic.

2.1 Definition And Causes of Personal Biases

To understand the implications of personal biases or stereotypes, it is imperative first to understand the inherent factors that influence the creation of personal bias in males and females. Eagly and Wood (2016) found that the development of beliefs imposed on children was due to the societal disposition of typical male and female roles. The beliefs introduced were defined as biases or stereotypes. Social role theory argued that stereotypes about men and women were based on observations and the innate tendencies to follow the understood characteristics of sex that appeared natural and inevitable (Bosak & Sczesny, 2011). These beliefs begin in childhood due to the physical differences in size and strength that allow men to be more efficient when completing physically demanding tasks. In addition, men were reported to be more competent, powerful, and capable of leading than women, who were attributed to caretaking roles (Bosak & Sczesny, 2011). Overall, biases developed throughout a child's growth can become deeply ingrained and unconsciously impact decision-making and behavior.

Poor hiring decisions and beliefs projected on an industry may lead to misrepresentation or limited diversity of genders and ethnicities. Within male-dominated industries (such as aviation), the roles that needed to be filled were associated with being more masculine-type, which led to unconscious bias, affecting hiring within these roles (Bozak & Sczesny, 2023; Casebolt, 2023). However, more initiatives have been taken recently to change these skewed workplace populations. Workforce diversity is defined as the differences between people within a particular group working together to enhance their performance and productivity (Trifilo & Blau, 2024). High workforce diversity was revealed to be desirable for industries, yet it might have been limited during the hiring process at all stages due to implicit bias. Casebolt (2023) interviewed 10 women in aviation careers, finding that each participant believed that unconscious barriers and biases existed against women in aviation. Overall, unconscious or implicit biases were indicated to be a factor in the gender gap that exists between men and women within aviation.

2.2 Flight Experience in A Certified Flight Instructor (CFI) Position

Flight experience has played a critical role in the aviation industry, particularly when evaluating candidates for a CFI position. King et al. (2021) emphasized that aviation experience is primarily measured by a pilot's total flight hours and certifications. The relationship between decision-making and interpretation abilities was statistically significant at $p = .01$, and the level of certification impacted overall pilot performance and safety. Student pilot's interpretation scores were lower than private instrument-rated pilots', $p = .03$, and private pilot scores were lower than commercial instrument-rated pilots, $p = .05$ (King et al., 2021). Inexperience has been deemed a high contributor to general aviation accidents, ranging from 50 to 350 flight hours, otherwise known as "the killing zone" (Craig, 2000, p.7). Both ideas aligned with the industry's emphasis on lack of experience. In fact, Gladwell (2008) wrote about a neurologist, Levitin, who explained that achieving mastery in a field and becoming a world-class expert comes from obtaining 10,000 hours of practice. Bosak and Sczesny (2011) found that previous hiring decisions favored candidates with higher flight hours, particularly in male-dominated fields like aviation. Their research highlighted the importance of experience, as higher hours were often perceived as an indicator of greater competence, which is critical in training future pilots. Li et al. (2001) further explored CFI's safety and instructional quality, leading to managing various flight situations in the context of pilot error, where they suggested that experience significantly reduces the likelihood of human errors, which have often been a consequence of insufficient training and inadequate decision-making. Therefore, pilots with low flight time experience are more susceptible to accidents and scrutiny than their counterparts with more flight time experience.

2.3 Gender Bias In Aviation and Effects

The aviation industry remains predominantly male, creating challenges for women entering the field. Stevenson et al. (2021) examined women's perceptions of the aviation workplace. They provided valuable insights into women's obstacles, reinforcing the need for increased awareness and policy reform to create a more inclusive work environment. These obstacles included sexual harassment, gender bias, negative perceptions, and fears of bringing up management concerns. Even though these women had reported being satisfied in their jobs and confidently being able to meet deadlines, they struggled in areas that appeared out of their control. By identifying the critical areas of concern reported by women, Stevenson et al. (2021) underscored the importance of addressing workplace culture to promote gender equality. Similarly, Chatterjee and Shenoy (2023) emphasized how workplace biases have hindered women's career growth and limited their advancement to leadership roles. LaBerge et al. (2024) found that women were more at risk of leaving their faculty jobs than men. They identified critical components to this increase in gendered attrition, including not feeling supported or valued for qualifications. Casebolt (2023) reported that women often had concerns about the gender gap, feeling outnumbered and lacking career advancement despite equal skill sets. These studies indicate that women still face challenges when entering and working within a male-dominated industry.

Perceptions from passengers also varied, depending on cultural background and conceptions of women's roles. Mehta et al. (2017) examined the perception of women in flight crews, which negatively influenced passengers' willingness to fly. However, compared to countries like India, Americans were more likely to support women in the flight deck due to proven success in other authority roles (Mehta et al., 2017). Vermeulen (2009) also reported that CFIs had more positive perceptions of female pilots' performance than commercial-rated pilots with less total flight time experience. Regarding industry success, increasing female representation in aviation, closing the gender pay gap, and promoting gender equity contribute to the industry's sustainability and operational success (Corazza, 2024). In line with global recommendations, fostering an inclusive environment can enhance performance and ensure long-term stability for the aviation sector. These findings aligned with prior research that sought to understand previous gender biases in hiring practices, thereby supporting the broader goal of improving representation and success in aviation.

2.4 Gender Gap in Collegiate Education

The gender gap that exists within the aviation industry has also been shown to appear within collegiate flight school programs. Students in these programs have indicated that women have been under-represented (Casebolt & Khojasteh, 2020). Multiple studies have shown that students believe a significant cause of this gap is the lack of female role models and instructors (Casebolt & Khojasteh, 2020; Turney et al., 2002). Other factors contributing to this gap are historical biases and the fact that male pilots are the majority within the industry (Casebolt & Khojasteh, 2020). Personal beliefs have been influenced by historical biases and developed over a long period from early education and throughout the advancement of a pilot's career, as discussed previously by Eagly and Wood (2016).

While strategies for reducing the diversity gap are being implemented, it remains to be seen where intervention can take place to promote more women into the aviation field and what it takes to succeed in the hiring process. Previous research suggests that implicit stereotypes implant false perceptions in children to grow up assuming prenotion gender roles. Aviation is a complex industry for women to enter and remain within. However, previously, experience has been shown to be an important quality for positions within the aviation industry. Therefore, this research seeks to understand if the next generation of pilots currently have differences in perceptions of applicants with gender and flight experience.

3. Methodology

The target population was all licensed pilots and hiring managers within the aviation industry in the United States. The accessible population was students 18 years or older enrolled in the a Part 141 collegiate program in Florida. A stratified cluster sample of pre-existing groups (core aeronautics classes) was used to collect a non-probability-based sample. Each class represented a different level of experience and provided a convenient cross-section of knowledge and experience within the program from first semester to final semester students. No identifying information was gathered; however, demographic information was collected, including biological gender at birth, total flight hours to date, ratings and certificates held, and the aeronautics class the participant was enrolled in.

In 2022, the collegiate population accessible at the Part 141 collegiate flight program in Florida was reported to be 2,965 students in total, 62.9% male and 37.0% female (Florida Institute of Technology, 2022). Within the aeronautics program, the gender ratio was even more skewed toward a higher enrollment of male versus female students, representing closer to the FAA estimate of about 10% (FAA, 2024). Aside from gender, about 46.2% of university students were from various ethnicities other than white and, therefore, compose one of the most diverse universities in the United States (Florida Institute of Technology, 2022). In the Spring of 2024, the aeronautics program reported approximately 578 undergraduate students attending, providing a subject pool of at least 250 participants to respond to the survey (Florida Institute of Technology, 2024). The natural diversity of this program has exposed students to differences and may encourage students to be more accepting of others than pilots existing within the industry today. This diversity and acceptance may inadvertently influence findings.

The questionnaire was administered online through Qualtrics and asked participants to rate brief applicant professional bibliographies based on their perceived qualifications for a CFI position. Qualtrics provided an easy distribution to participants and ensured an equal number of responses were collected for each hiring scenario. The questionnaire used items for perceived employability created by Bosak and Sczesny (2011) that were validated and published through peer reviewed as items effective in quantifying employability. These items asked participants to list their certainty of hiring a candidate for a leadership position or of shortlisting a candidate from (-5) to (5) in their previous study. However, these two items were modified slightly for the purpose of this study to rate the certainty of hiring for a CFI position and the certainty of having the applicant be a personal instructor using a scale of (-5) to (5). These items provided similar results as they are both ratings of employability, ultimately improving validity. Following Bosak and Scesny's (2011) proposed methodology, two items were averaged to yield the employability rating.

The IRB approved the exemption application (24-188) before the study began. Professors of applicable classes were emailed to request permission to visit and recruit participants. The recruitment method included an in-person public announcement and learning management system announcement in core aeronautics classes. A printed QR code was handed out to participants in classes to distribute the Qualtrics questionnaire. The questionnaire presented brief professional bibliographies of pilots with gender-neutral names, differing genders (he/him or she/her pronouns), and differing experience levels (300 or 1,000 hours, selected as typical low and high time flight experience for first-time CFI hires). Participants were randomly assigned to view two of four scenarios, one low time applicant, and one high time applicant in each questionnaire, and a random gender in each bibliography. Low and high time applicants were randomly presented to avoid the order effect.

Statistical analyses were performed using RStudio version 2024.09.1+394. The results from the questionnaire from Qualtrics were transferred into an Excel spreadsheet and saved for use in RStudio to calculate descriptive and inferential statistics. A one-way ANOVA was conducted due to having one categorical independent variable with four hiring scenarios and one numerical dependent variable (employability). Finally, Tukey's pairwise comparison was used to determine which pairs were significantly different, and an effect size was determined through eta squared.

4. Results

A total of 405 responses were collected from students enrolled in core aeronautics classes at the Part 141 flight school, reflecting a large proportion of the enrolled student population (i.e., accessible population). Out of the approximately 578 undergraduate students enrolled on campus, 458 were enrolled in the classes visited for recruitment (Florida Institute of Technology 2024). This study achieved an overall response rate of 94.32%.

The gender distribution in survey responses was 78.47% male and 21.52% female, closely mirroring the collegiate flight program's demographics. At the institutional level, the gender ratio is 62.9% male to 37% female (Florida Institute of Technology, 2022). This gender disparity aligns with the industry's national averages and supports the relevance of examining gender perceptions within this population.

To ensure participants were actively aware of the applicant's gender, a variable check was presented in the questionnaire. This was a single item, which asking the applicant's gender, immediately following the rating of each CFI applicant. Participants were aware of the applicant's correct gender 90% of the time, indicating a high level of attention, and appropriate manipulation of gender in the scenarios.

To provide insight into participant perceptions across different hiring scenarios, descriptive statistics were calculated for each category: High Flight Time Male (HM), High Flight Time Female (HF), Low Flight Time Male (LM), and Low Flight Time Female (LF). Descriptive statistics are presented for rating of certainty to have the applicant as their personal CFI (Table 1), rating of certainty for hiring (Table 2), and employability, the average of these two questions (Table 3). Note that all hiring scenarios spanned the entire range of responses, and the means for high-time hiring scenarios were all positive and close to 4, while the means for low-time hiring scenarios were all positive and close to 2.5. The standard deviation was highest for low-time hiring scenarios.

Figure 1 shows the average ratings of different applicants for a CFI position on two employability items (Tables 1 & 2): certainty of hiring the applicant and certainty of wanting the applicant to be a personal CFI. The ratings of each item (certainty of hiring and certainty of personal CFI) were averaged [illegible] 3.

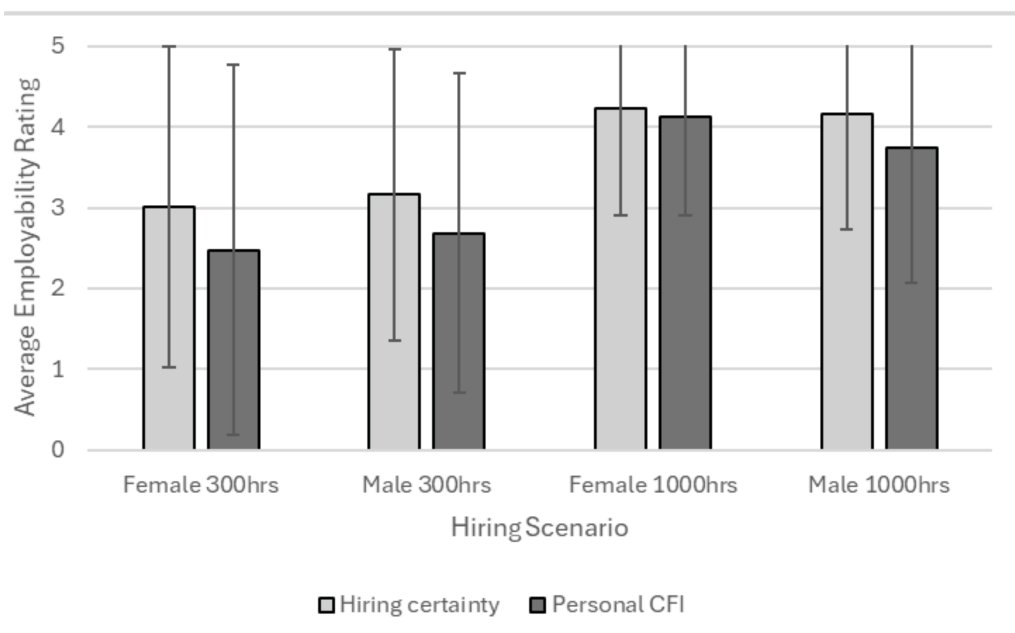

Figure 1. Certainty Of Hiring the CFI Applicant and Certainty of Personal CFI By Hiring Scenario

Note: Error bars indicate one standard deviation.

Table 1. Descriptive Statistics for Rating of Certainty to Have Applicant as a Personal CFI

Hiring Scenario	Mean	Median	Mode	Standard Deviation	Min	Max
HF	4.13	4.0	4	1.23	-5.0	5.0
HM	3.74	4.0	5	1.68	-5.0	5.0
LF	2.48	3.0	4	2.29	-5.0	5.0
LM	2.68	3.0	4	1.98	-5.0	5.0
Overall	3.25	4.0	5	1.96	-5.0	5.0

Note: The scenarios were High Flight Time Male (HM), High Flight Time Female (HF), Low Flight Time Male (LM), and Low Flight Time Female (LF).

Table 2. Descriptive Statistics for Rating of Certainty to Hire Applicant

Hiring Scenario	Mean	Median	Mode	Standard Deviation	Min	Max
HF	4.22	5.0	4	1.31	-5.0	5.0
HM	4.16	5.0	5	1.43	-5.0	5.0
LF	3.01	3.0	4	1.98	-5.0	5.0
LM	3.16	4.0	4	1.81	-5.0	5.0
Overall	3.64	4.0	5	1.74	-5.0	5.0

Table 3. Descriptive statistics for average rating of hiring applicant and personal CFI

Hiring Scenario	Mean	Median	Mode	Standard Deviation	Min	Max
HF	4.15	4.5	4	1.30	-5.0	5.0
HM	3.95	4.0	5	1.44	-5.0	5.0
LF	2.74	3.0	4	2.055	-5.0	5.0
LM	2.92	3.5	4	1.73	-4.5	5.0
Overall	3.44	4.0	5	1.77	-5	5.0

The ANOVA assumptions were checked and met except for the following. The Shapiro-Wilk's test for normality indicated hiring ratings were not normally distributed ($p < .001$). However, given the robust sample size ($n = 405$), the central limit theorem can be applied. Additionally, Levene's test of homogeneity of variance yielded a result of $p < .001$, but there were equal numbers of responses in each group allowing the analysis to proceed.

The ANOVA revealed a statistically significant difference in employability ratings by hiring scenarios, $F(3, 401) = 37.23$, $p < .001$. This supports the hypothesis that there would be a difference in ratings by hiring scenario. These findings indicate that participants evaluated CFI candidates differently based on their hiring scenarios. Given the significant ANOVA results, a Tukey's post hoc pairwise comparison was conducted (see Table 4), identifying significant differences ($p < .001$) between all scenario pairs except for between High Flight-Time Female (HF) and High Flight-Time

Male (HM) and Low Flight-Time Male (LM) and Low Flight-Time Female (LF). The eta squared was .12, which is a medium effect size.

Table 4. Pairwise Comparison of Hiring Scenarios

Hiring Scenario	*p* Adjusted
HM – HF	.65
LF – HM	<.001
LM – HF	<.001
LM – HM	<.001
LM – LF	.70

Note: HM (high flight-time male), HF (high flight-time female), LM (low flight-time male), LF (low flight-time female).

5. Discussion

This study explored hiring biases among collegiate Flight 141 students to understand the potential reasons behind the low representation of women in the aviation industry and why this percentage has not increased significantly (FAA, 2024). The study looked at four hiring scenarios that varied flight experience and gender of CFI applicants, both of which are factors that may be related to employability to determine whether they are perceived differently by current collegiate aviation students. The CFI is the typical next career stage for a flight student.

The hypothesis was that there would be a significant difference in employability by hiring scenario. The ANOVA showed supported this expectation, demonstrating a statistically significant difference in employability ratings by hiring scenario ($p < .001$). This statistically significant difference provided grounds to accept the alternative hypothesis and reject the null hypothesis. The Tukey's pairwise test showed that there was a statistically significant difference in hiring ratings between all scenario pairs ($p < .001$; Table 4), except for those with equal flight experience (HM-HF and LM-LF). The descriptive statistics (Tables 1-3, Figure 1) illustrated that on average, participants rated all scenarios positively. Both hiring certainty and personal CFI certainty had little difference visually within each hiring scenario (Figure 1). The medium effect size also indicates that there is a practical difference in the hiring selection between CFI candidate scenarios with different experience levels.

These results suggest that Part 141 students prioritized flight experience over gender when evaluating employability. High-flight-time candidate scenarios consistently received higher ratings than low-flight-time scenarios, irrespective of gender. This aligns with prior research (Bosak & Sczesny, 2011), including a correlation between higher flight hours of candidates and hiring decisions in male-dominated fields, and emphasizing the importance of experience in hiring decisions for male-dominated industries. It has also been suggested that experience reduces human error and therefore pilots with less experience should be more scrutinized (Li et al., 2001). Therefore, it would be expected that student pilots would also consider more experienced pilots to be better suited for a CFI position. The absence of significant gender-based differences in scenario ratings may indicate that Part 141 flight students evaluate candidates more objectively, at least in controlled academic settings, potentially mitigating any implicit gender biases. Specifically, the high time scenarios with 1,000 hours of flight time received higher ratings compared to those with only 300 hours, highlighting the importance attributed to experience when evaluating potential CFIs. However, there was a negligible difference in employability rating between scenarios with the same flight time, indicating that gender of applicant did not substantially influence the ratings.

Flight experience had a positive effect on employability ratings, with students evaluating high time scenarios as more certain hires and more certain to be their own CFI. Each professional bibliography was designed to be exactly the same with two exceptions, flight experience and gender, to control for other variables that were not being tested. Random assignment of the professional bibliographies avoided any order effects.

There are some confounding variables that may have influenced responses. Social desirability, which implies that respondents will pick the answer that they believe society deems appropriate, may have been subconsciously working within students as they answered a questionnaire. This could also have combined with the researcher effect as three researchers took turns being present as the questionnaire was distributed (for almost all classes, at least one female researcher was present). In addition, the university at which the responses were collected has a high diversity when compared to other flight programs. As discussed before, the ratio of male to female was 62.9% male and 37.0% female, with one of the most diverse college campuses within the United States, possibly improving overall acceptance and removing biases that may have existed. The sample's representativeness was evaluated by examining its demographic composition and comparing it to the broader population of collegiate Part 141 students. Key metrics, such as gender, age, and other relevant factors, were analyzed to determine alignment with the overall population. The results are most generalizable to students within similar collegiate flight training programs with comparable demographic and structural characteristics. However, the results are interesting as they imply a lack of gender bias within the studied collegiate flight program.

Given the sample population, the findings are not generalizable directly to commercial pilot hiring processes, and conflict with prior research that highlighted the challenges of women in aviation, namely gender bias and not fitting into the male dominated work culture (e.g., Casebolt, 2023; Chatterjee & Shenoy, 2023; Stevenson et al., 2021). Davey and Davidson (2000) studied women at a commercial airline qualitatively and found that while gender bias had improved over time, females in aviation still had to prove themselves, despite their competency, and tended to adapt to the predominantly male culture. Likewise, Opengart and Ison (2016) found through their mixed methods approach that women in aviation in Canada and the US struggled with the male-dominated culture, and even had a difficult time envisioning themselves in their roles because of a lack of models. They recommended a focus on both hiring women and support throughout the male-dominated career path, especially organizational and management support, and improving awareness of female role models (Opengart & Ison, 2016). These studies all indicate the persistence of barriers for women in aviation.

This study provided a snapshot of the current student perceptions of CFI applicants; replicating this study with professional hiring committees or current commercial airline pilots could provide a more accurate assessment of gender bias and experience in real-world hiring decisions. Replication across multiple campuses would examine whether gender bias varies, depending on institutional or cultural diversity. Longitudinal studies are recommended to track hiring outcomes for pilots with varying experience levels and demographic characteristics. This approach would help determine whether perceptions observed in collegiate flight programs align with actual hiring outcomes in the aviation industry. Interviewing hiring committees about the reasons why they decided to select applicants would also clarify the factors driving hiring decisions.

Theoretical and practical applications of these findings include the development and maintenance of fair hiring practices within flight schools and training programs. The lack of a gender bias in this study indicates that the next generation is focusing on flight experience as a measure of whether a candidate is hirable. These practices can ensure a diverse and capable pilot workforce that aligns with Title VII of the Civil Rights Act of 1964, which prohibits employment discrimination based on sex (EEOC, 1964). Such changes have broader implications for aviation recruitment and workforce diversity, informing future policy decisions aimed at increasing female representation in the industry.

6. Disclaimer Statements

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Conflict of Interest: None

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