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Sentiment Analysis of AI's Impact on Labor Market: Opportunities and Threats

Rhyan C. de Loyola[1]* | Edreian R. Escototo[1] | Nahdem C. Columida[1] | Eddie G. de Paula Jr.[1]

[1]University of St. La Salle, Bacolod City, Negros Occidental, 6100, Philippines

***Correspondence:** s2302894@usls.edu.ph

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Abstract

Artificial Intelligence (AI) has emerged as a transformational force, reshaping enterprises, businesses, and industries through worldwide dynamic workforce innovation. This study analyzed sentiments expressed by users on the X (formerly Twitter) platform regarding AI's impact on the labor market, mainly focusing on job displacement and employment opportunities. This research aims to identify the range of sentiments expressed, determine the underlying emotional valences, and explore the implications of these sentiments on workforce adaptation, including an analysis of the opportunities and threats posed by AI. Using a reliable open dataset of tweets, the study employed Plutchik's model to categorize emotional states. It assessed them using valence-based and emotion-detection algorithms implemented in the R programming language. The sentiment analysis revealed a predominance of positive sentiments, with many users expressing optimism about AI's potential to enhance efficiency and create new job opportunities. However, significant concerns about job displacement and skills obsolescence were also noted. The analysis also highlighted several opportunities, including AI's potential to increase efficiency, create new job roles related to AI technologies, and drive innovation across various sectors. At the same time, threats were identified, such as the risk of job displacement due to automation, the need for continuous upskilling to prevent skills obsolescence, and the potential for widening economic inequality between those who can adapt to technological advancements and those who cannot. These findings align with MacKuen's theory, which suggests that as individuals become more acquainted with new technologies, their perception generally becomes more optimistic. While AI is often seen as a disruptor, it is also recognized as an opportunity for growth and innovation. The readiness of users to embrace change, acquire new skills, and adapt to industry trends highlights the importance of fostering resilience and continuous learning. This adaptability suggests that AI is increasingly being perceived not as a threat but as a catalyst for development and labor force advancement, positioning it as a driving force for future workforce dynamics.

1 | INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force of the 21st century, fundamentally reshaping industries and the global workforce [1]. With its capacity to drive unprecedented efficiency, innovation, and economic growth, AI also brings considerable challenges, particularly regarding its potential impact on job displacement and the necessity for workforce adaptation [2], [3]. Understanding the varied sentiments surrounding AI's influence on employment is essential for businesses, policymakers, and individuals as they prepare to navigate the opportunities and disruptions AI presents [4], [5].

Projections regarding AI's impact on the labor market show considerable variation, reflecting both optimism and concern. According to Lindner [6], by 2030, as much as 14% of the global workforce could face job displacement due to the rise of AI and automation, highlighting the disruptive potential of these technologies. In the United States alone, AI was projected to eliminate 1.3 million jobs by the end of 2020, a

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stark indicator of the immediate impact AI could have on the job market. However, this disruption is not solely negative. AI was also forecasted to generate approximately 58 million new jobs globally between 2018 and 2022, emphasizing the technology's capacity to create new roles and industries. This dual effect underscores the complexity of AI's influence on employment, as it simultaneously drives innovation and job creation while displacing traditional roles. By 2025, AI could replace 16% of jobs in the U.S., further illustrating its disruptive nature. Still, these projections also suggest opportunities for workforce transformation, with the potential for new AI-related jobs to emerge as industries adapt to technological advancements.

The Philippine News Agency [7] projects that by 2027, the combined influence of AI and economic factors could lead to the displacement of 83 million jobs in the Philippines while simultaneously creating only 69 million new positions. This imbalance would result in a net deficit of 14 million jobs, representing approximately 2% of the nation's workforce, signaling a significant challenge for the country's employment landscape. These figures highlight the delicate balance between the forces of job displacement and job creation as AI continues to reshape industries. While there is optimism about the potential for AI to drive innovation and stimulate employment growth in new sectors, concerns about economic stability remain prominent, particularly for those whose jobs are most at risk of automation.

While extensive research has explored AI's broader impact on employment, there is a notable gap in sentiment analysis specifically focused on public perceptions of AI-driven job displacement and workforce adaptation. Few studies have delved into the emotional responses to these changes despite growing recognition of the importance of understanding individuals' and communities' complex reactions to AI's evolving role in the labor market. Lindner and the Philippine News Agency emphasize that significant job losses due to AI are anticipated. Yet, the public perception of this issue remains understudied, highlighting the need for deeper investigation into citizen reactions.

To address this gap, the present study conducts a sentiment analysis using real-time data from the X platform (formerly Twitter), a valuable resource for capturing a broad spectrum of opinions and sentiments from diverse users [8]. Tweets are particularly suitable for sentiment analysis due to their brevity and conciseness [9], facilitating the efficient processing of large datasets [10]. This research explores public perceptions of AI's impact on employment, focusing on job displacement and workforce adaptation. Key objectives include identifying positive, negative, or neutral dominant sentiments about AI-driven job displacement and adaptation. Additionally, the study compares public perceptions with current projections of AI's effects on job displacement and creation.

Analyzing this data, the study provides critical insights into public attitudes toward AI about employment, revealing optimism for technological advancement and concerns about job security. Hence, policymakers and businesses should design strategies to balance AI's innovative potential with efforts to mitigate its disruptive impacts on jobs. Moreover, understanding these public sentiments can guide more effective strategies for promoting workforce resilience in the face of rapid technological change.

2 | METHODOLOGY

A. Research Design

The methodology of this study followed a four-phase process combining a lexicon-based and valence-based approach to improve sentiment analysis accuracy [11]. The first phase involved collecting and preprocessing data from X, focusing on AI-related job displacement and workforce adaptation, followed by text preprocessing. A sentiment lexicon specific to AI and employment was constructed in the second phase, containing keywords to classify tweets as positive, negative, or neutral. The third phase evaluated the emotional intensity of critical phrases for sentiment classification. Finally, the fourth phase involved analyzing and visualizing the results.

B. Data Collection

The first phase of the methodology focused on data collection, utilizing Python and the Tweepy API, a powerful tool for accessing real-time tweet data from X [11]. The researchers employed Python to integrate the Tweepy API, incorporating a carefully selected set of keywords and hashtags into the algorithm. The following keywords were selected during data collection: "Technological Disruption," "Job Automation," "Employment Transformation," "Job Market Dynamics," "Employment and Automation," "Job Economics with AI," "AI Job Displacement," "AI Workforce Evolution," as well as two relevant hashtags. Only tweets posted in the last five years (from 2021) were included in this study to capture current trends and opinions pertinent to the central topic of this study. These keywords ensured a broad and relevant dataset reflecting discussions on AI's impact on employment. Figure 1 presents the flowchart for data collection.

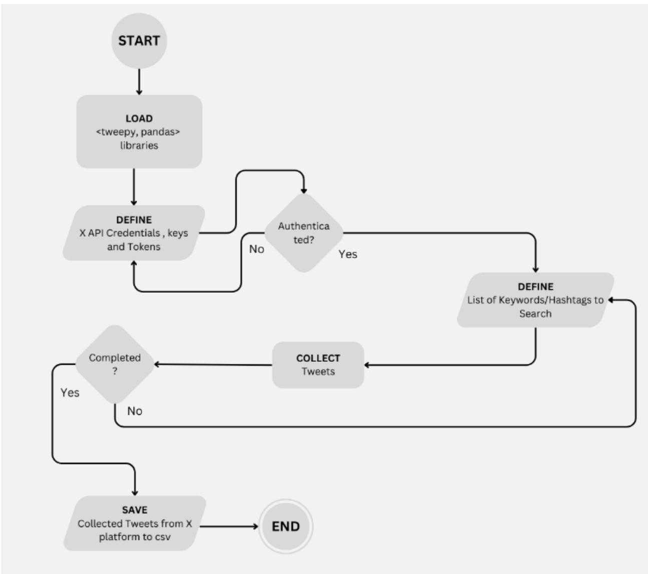

Figure 1. Data Collection Flowchart using Tweepy API.

After executing the algorithm, the collected tweets were stored in a comma-separated values (CSV) file, offering a convenient and portable format for further analysis and easy sharing. This format facilitated efficient data processing while ensuring compatibility with various analytical tools. Table 1 presents the distribution of the initial data collected from X.

TABLE 1. Distribution of Extracted Tweets from X.

Class	Keyword / Hashtags	*N*	%
Keyword	Technological Disruption	100	11.66
Keyword	Job Automation Effects	99	11.54
Keyword	Employment Transformation	101	11.77
Keyword	Job Market Dynamics	100	11.66
Keyword	Employment and Automation	101	11.77
Keyword	Job Economics with AI	60	6.99
Keyword	AI Job Displacement	62	7.23
Keyword	AI workforce Evolution	36	4.20
Hashtags	#FutureofWork	100	11.66
Hashtags	#EmploymentTransformation	99	11.54
TOTAL		**858**	**100**

N Data Count, % Percentage

The table presents the distribution of 858 tweets extracted from X, segmented by keywords and hashtags. Notably, "Employment Transformation" and "Employment and Automation" appeared in 101 samples, highlighting a significant focus on these topics in the discussions. Similarly, keywords like "Technological Disruption," "Job Automation Effects," and "Job Market Dynamics" were prevalent, each featured in approximately 100 samples. The two hashtags also garnered notable attention, comprising 11.66% of the dataset.

After extracting the initial dataset, a filtering process was applied to ensure the relevance of the final dataset. This process was designed to exclude samples that do not directly relate to the central topic of this study. For transparency and accountability, detailed documentation of the data collection process was kept, including the inclusion and exclusion criteria, as shown in Table 2. The researchers manually applied these criteria, conducting a thorough review to ensure that only relevant tweets were retained. This meticulous approach safeguarded the integrity of the dataset, ensuring it aligned with the established research objectives.

TABLE 2. Inclusion and Exclusion Criteria.

Inclusion Criteria		**Exclusion Criteria**	
1.	English tweets containing the keywords selected for this study	1.	Non-English tweets.
2.	Retweets offer unique perspectives.	3.	Irrelevant tweets.
4.	Diverse Twitter users, including individuals, organizations, and verified accounts.	2.	Duplicate tweets or retweeted tweets.
5.	Both positive and negative sentiments towards AI-induced job displacement.	3.	Spam or promotional content.
6.	Tweets posted from 2021 to 2024 (August).	4.	Tweets posted before 2021.

After thoroughly assessing the initial dataset based on the established inclusion criteria, the final pool of qualified samples has been identified, ensuring that only relevant and meaningful contributions were retained for further analysis. This meticulous filtering process was designed to eliminate irrelevant, duplicated, or off-topic content, thus enhancing the overall quality and reliability of the data. As a result, Table 3 presents the complete distribution of these tweets, including 292 qualified samples. This final dataset forms the core for the sentiment analysis in this study, providing a focused and representative collection of public opinions that will offer valuable insights into the broader discourse surrounding AI and its effects on the job market.

TABLE 3. Distribution of the Final Dataset.

Class	Keyword / Hashtags	*N*	%
Keyword	Technological Disruption	12	4.11
Keyword	Job Automation Effects	75	25.68
Keyword	Employment Transformation	24	8.22
Keyword	Job Market Dynamics	28	9.59
Keyword	Employment and Automation	42	14.38
Keyword	Job Economics with AI	24	8.22
Keyword	AI Job Displacement	2	0.68
Keyword	AI workforce Evolution	14	4.79
Hashtags	#FutureofWork	40	13.70
Hashtags	#EmploymentTransformation	31	10.62
TOTAL		**292**	**100**

N Data Count, % Percentage

C. Pre-Processing

R has proven highly effective and versatile in statistical computing and data analysis, offering significant advantages for various tasks, including sentiment analysis [12]. Its capabilities make it well-suited for handling textual data, enabling robust and efficient processing [13]. During the pre-processing phase, ensuring the cleanliness and quality of the dataset is crucial before conducting further analysis. This involves eliminating noise such as retweets, spam, and irrelevant content, thereby refining the dataset to focus exclusively on tweets directly relevant to the research topic. The analysis becomes more accurate and meaningful by narrowing the dataset. Figure 2 illustrates the various activities in the pre-processing phase, providing a visual overview of how the raw data was transformed into a clean, relevant dataset ready for sentiment analysis.

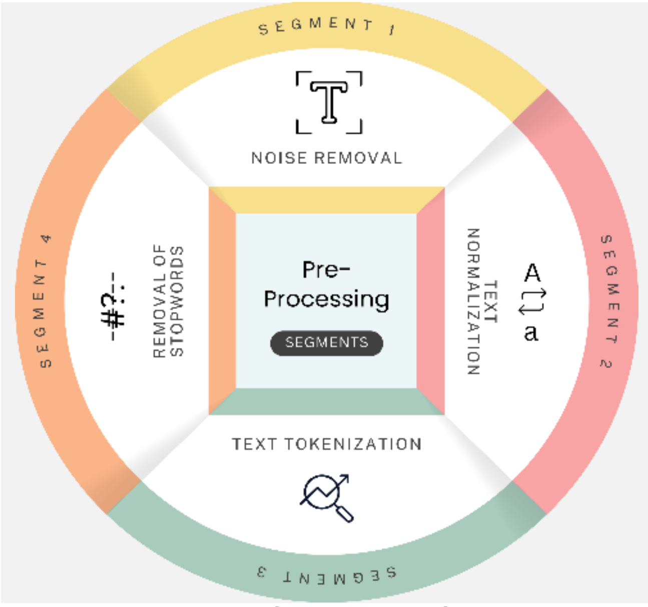

Figure 2. Activity Segments in the Pre-Processing Phase.

Noise removal is a crucial step in preprocessing textual data for sentiment analysis, as such data often contains various forms of irrelevant or redundant information. Common noise sources include frequent but insignificant words, punctuation marks, special characters, URLs, email addresses, HTML tags, and numbers. The dataset becomes more focused by filtering out these unnecessary components, allowing the sentiment analysis to yield more reliable and meaningful results. Figure 3 presents a flowchart outlining the noise removal process.

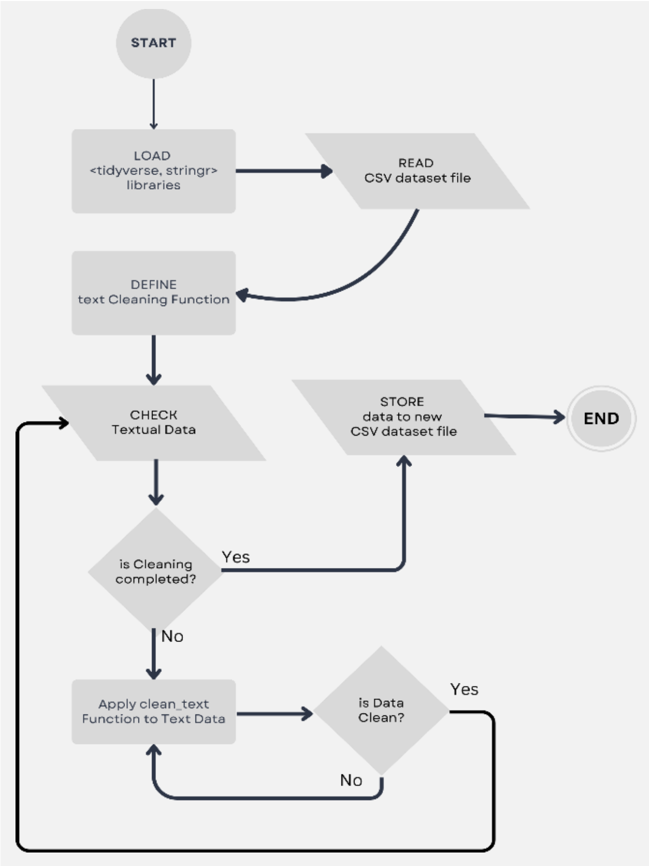

Figure 3. Noise Removal Process Flowchart.

The algorithm for data cleaning was implemented using the R language, leveraging the necessary libraries tidyverse and stringr. After loading the dataset from a CSV file, a custom function was developed to clean the text by systematically removing URLs, hashtags, mentions, special characters, and unnecessary spaces. Once the cleaning process was complete, the refined data was saved to a new CSV file.

Following noise removal, the text normalization process was implemented as a critical step to standardize the textual data and ensure consistency across the dataset. This process involved transforming the text into a uniform format using techniques such as lowercasing, stemming, lemmatization, and handling special characters and numerical values [14], [15]. These standardization techniques are vital for improving the precision of the sentiment analysis and enhancing the model's overall performance. The sub-processes of text normalization included:

1. **Handling of Special Characters**: This step addressed special characters, punctuation, and numerical values. Special characters and punctuation marks were removed or replaced with spaces to prevent them from interfering with the analysis. Numerical values were either converted into a standardized format or removed from the dataset to maintain focus on the textual content.

2. **Lowercasing**: All text was converted to lowercase, ensuring uniformity in word representation. This approach treats words like "Artificial" and "artificial" as the same, avoiding token duplication and enhancing analysis accuracy.

3. **Stemming**: Words were reduced to their root or base form by removing suffixes and prefixes. For example, "working," "work," and "worker" all stemmed from the base form "work," helping to streamline the dataset by merging similar words.

4. **Lemmatization**: A more advanced normalization technique, lemmatization, mapped words to their canonical form, considering context and meaning. Unlike stemming, lemmatization ensures that different inflected forms of a word, such as "am," "are," and "is," are all represented by a single token, "be," resulting in a contextually accurate analysis.

Text normalization plays a significant role in textual analysis, ensuring data is consistently processed and standardized for practical analysis. By leveraging the capabilities of the R language and employing these text-normalization algorithms, the textual data was preprocessed efficiently, significantly improving the quality, reliability, and accuracy of the resulting insights and conclusions. Figure 4 presents the text normalization activity flowchart.

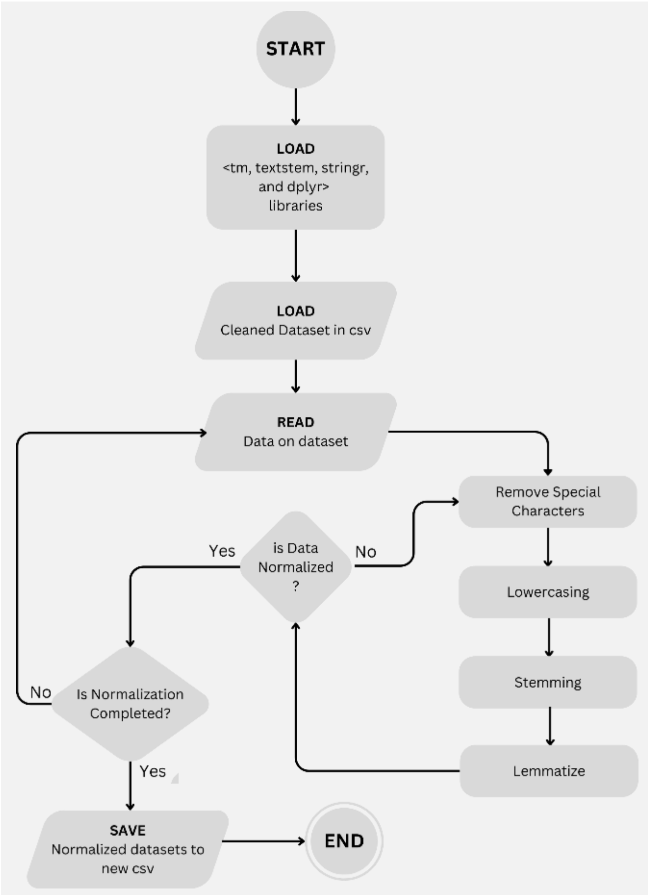

Figure 4. Text Normalization Flowchart.

After text normalization, the data undergoes tokenization, which involves breaking down the samples into individual words or phrases, known as tokens [16]. This segmentation enables the extraction of insights at a granular level, gaining a deeper understanding of the language used and the sentiments expressed within the dataset. R programming language was used in this phase, which provides a complete toolkit for preprocessing, analyzing, and visualizing tokenized text data. Figure 5 presents the Text Tokenization Flowchart.

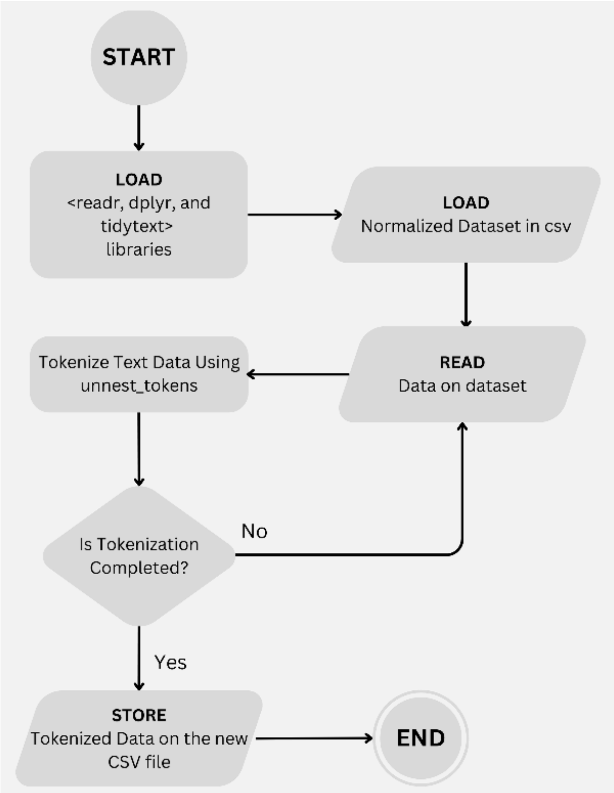

Figure 5. Text Tokenization Flowchart.

Stopwords are sets of ubiquitous terms like "the," "is," "in," "and," and "of" that are commonly found in text but often carry little value about the content. Removing stopwords is a fundamental preprocessing step that helps reduce the text data's dimensionality, enhancing its processing reliability. Figure 6 presents the Stopword Removal Flowchart.

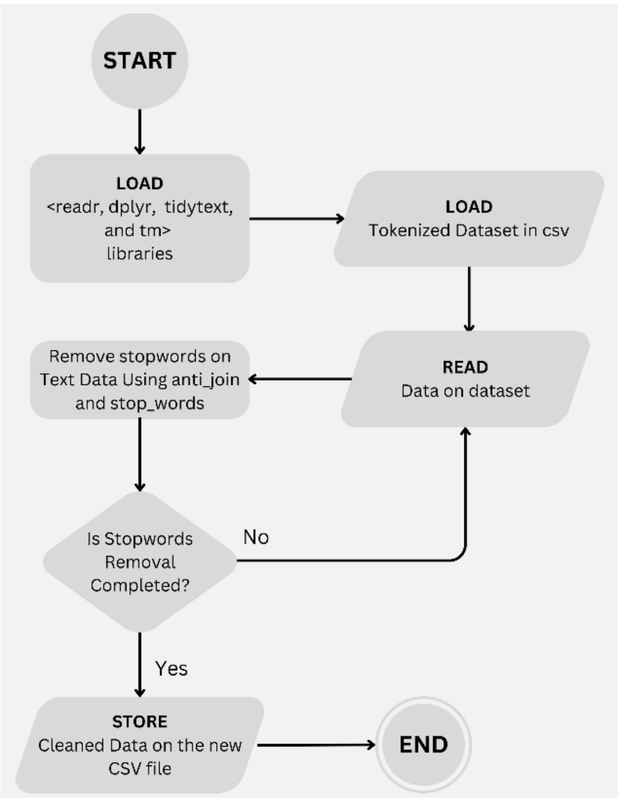

Figure 6. Stopword Removal Flowchart.

D. Sentiment Analysis

Plutchik's wheel of emotions is a theoretical model developed by psychologist Robert Plutchik, which primarily categorizes human emotions into eight primary bipolar dimensions: joy versus sadness, trust versus disgust, fear versus anger, and surprise versus anticipation [17]. Plutchik's model was selected for this study due to its comprehensive approach to categorizing and understanding human emotions. Unlike simpler sentiment analysis models that only differentiate between positive and negative sentiments, Plutchik's wheel captures the complexity of emotional experiences [18]. Table 4 presents the primary and secondary emotions according to Plutchik's model.

TABLE 4. Plutchik's Model of Emotions.

Primary Emotion	Definition
Joy	A feeling of great pleasure and happiness.
Trust	Confidence in or reliance on someone or something.
Fear	An unpleasant emotion is caused by the belief that someone or something is dangerous, likely to cause pain or a threat.
Surprise	A sudden feeling of astonishment or shock due to an unexpected event.
Sadness	A feeling of sorrow or unhappiness.
Disgust	A strong feeling of aversion or repulsion towards something.
Anger	A strong feeling of annoyance, displeasure, or hostility.
Anticipation	The expectation or prediction of something that might happen.

Secondary Emotion	Combination of Primary Emotions	Definition
Love	Joy + Trust	Deep affection and care towards someone or something.
Submission	Trust + Fear	Acceptance or yielding to a superior force or the will or authority of another person.
Awe	Fear + Surprise	A feeling of reverential respect mixed with fear or wonder.
Disapproval	Surprise + Sadness	An unfavorable opinion or feeling towards something or someone.
Remorse	Sadness + Disgust	Deep regret or guilt for a wrong committed.
Contempt	Disgust + Anger	The feeling that something or someone is beneath consideration or worthless.
Aggressiveness	Anger + Anticipation	A readiness to attack or confront.
Optimism	Anticipation + Joy	Hopefulness and confidence about the future or success of something.

In sentiment analysis, valence refers to the emotional polarity of a sentiment, categorizing it as positive, negative, or neutral [19]. Positive valence includes emotions generally associated with pleasant experiences like love, awe, optimism, joy, and trust. Negative valence, on the other hand, encompasses emotions linked to unpleasant experiences like disapproval, remorse, contempt, anger, and sadness. Neutral valence emotions, such as submission and surprise, can vary based on context and are not inherently positive or negative. Plutchik's model categorizes eight primary emotions and their opposites, creating a spectrum of 16 emotions grouped under positive, negative, or neutral valences, reflecting the broad range of human feelings [20].

D. Data Visualization

Data visualization provides a graphical representation of sentiment scores and distributions, making it easier to interpret sentiment-related insights [18]. These scores, generated using the Plutchik model, were initially stored in a CSV file and later processed and aggregated to ensure accuracy and consistency before visualization. Canva was used for data visualization. Annotations and explanatory text were added to provide context and facilitate the interpretation of the percentage distributions. Once the visualizations were completed, they were carefully reviewed for accuracy and readability, with refinements to ensure the visual effectively conveyed the sentiment analysis results.

3 | RESULTS AND DISCUSSIONS

The sentiment analysis results revealed a complex emotional landscape regarding AI's impact on employment. As shown in Figure 7, 21.9% of respondents expressed trust, indicating optimism about AI's potential to drive innovation and bring positive economic changes. This finding aligns with literature suggesting that AI is often seen as a tool for enhancing productivity and creating new opportunities across various industries [4], [1]. The second most common emotion, anticipation (18.1%), reflects excitement and readiness for AI-driven change, signaling that a substantial portion of the public is open to embracing AI's advancements. This supports research indicating that many workers are eager to adapt to new technologies, recognizing the transformative potential of AI in reshaping industries and improving efficiency [21].

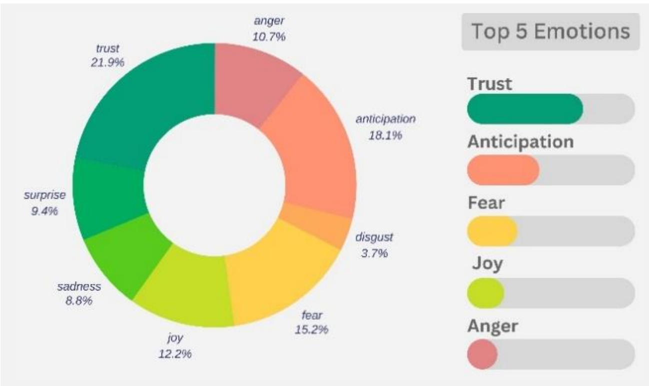

Figure 7. Sentiment Distribution.

However, fear in 15.2% of the sentiments highlights concerns about job displacement and the obsolescence of specific skills due to automation and AI-driven processes [3], [5]. These findings underscore the anxiety surrounding the future of work in the age of AI, particularly in industries highly susceptible to automation. Similar trends have been noted in studies emphasizing the challenges of workforce displacement and the need for upskilling to mitigate these risks [3]. In addition to fear, anger (10.7%) reflected frustrations over perceived injustices in AI's influence on job dynamics, such as wage disparities or the concentration of benefits within specific sectors [6]. These emotions reinforce concerns that AI could exacerbate inequalities, a point emphasized in recent discussions on AI ethics and its broader social implications [22].

On the other hand, joy (12.2%) indicates that some individuals are already experiencing the benefits of AI, particularly in sectors where AI facilitates innovation and improves work environments [2]. Surprise (9.4%) likely reflects reactions to unexpected developments in AI, while sadness (8.8%) points to concerns about the potential negative impact on human livelihoods. These mixed sentiments suggest that while many view AI as an opportunity, there are significant concerns regarding its disruptive potential [5], [6].

These findings highlight the need for a balanced approach to AI integration in the workplace. While optimism and excitement prevail, the notable levels of fear, anger, and sadness highlight the importance of addressing the negative impacts of AI adoption. Policymakers and businesses must prioritize strategies such as upskilling and reskilling programs, as recommended by [21], to ensure that workers are prepared for the changing job market.

The valence analysis reveals a predominantly positive sentiment, with 52.3% of respondents expressing optimism and acceptance of AI's impact on the labor market, indicating that many view AI as a catalyst for innovation, efficiency, and new job creation, as shown in Figure 8. This widespread positivity likely stems from the perception that AI technologies can significantly enhance productivity and contribute to economic growth by introducing new opportunities in various sectors [4], [1]. These findings align with studies highlighting AI's transformative potential to revolutionize industries, drive advancements, and bolster workforce dynamics by creating new roles [3], [2].

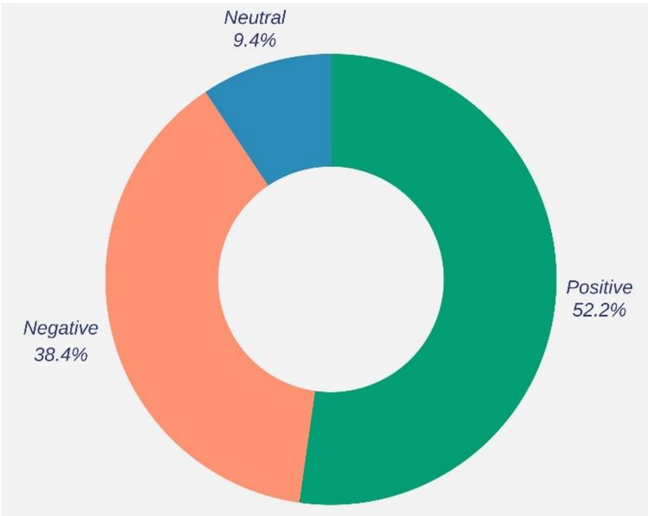

Figure 8. Results of Valences.

However, negative sentiments (38.4%) reveal significant concerns about AI's broader impact on the labor market. These concerns revolve around the fear of job displacement, the obsolescence of skills, ethical implications, and potential socio-economic divides as AI replaces traditional roles in many industries [5], [6]. This negativity suggests that while some individuals are optimistic, others are worried about the rapid integration of AI and its potentially disruptive effects. Failure to address these challenges could lead to a polarized workforce, where benefits are concentrated in a few sectors while others face job insecurity and instability [22].

Neutral sentiments represented 9.4% of the responses, indicating mixed emotions and balanced viewpoints toward AI. These neutral responses reflect a cautious optimism, where individuals recognize AI's potential benefits but remain mindful of its drawbacks. This finding suggests that some individuals take a pragmatic approach to AI, weighing its opportunities against its challenges more accurately. This cautious outlook aligns with research emphasizing the need for strategic planning and thoughtful integration of AI in the workplace to mitigate unintended consequences while promoting growth [21].

4 | CONCLUSION

This study explored public perceptions of AI and its impact on the labor market by analyzing sentiments expressed on X. The sentiment analysis revealed a complex emotional landscape, with most respondents expressing positive sentiments, such as optimism and trust toward AI's potential for innovation, job creation, and economic growth. However, significant negative sentiments were also observed, highlighting public concerns about job displacement, skills obsolescence, and socio-economic inequalities caused by AI adoption. Fewer respondents expressed neutral sentiments, indicating a cautious optimism and balanced view of AI’s potential benefits and risks.

The findings of this study offer valuable insights into the varying public opinions on AI's disruptive and transformative effects on employment. However, several limitations must be acknowledged. The dataset is limited to public opinions expressed on X, which may not fully capture the perspectives of all stakeholders affected by AI's impact on jobs. Additionally, the analysis focused primarily on English-language tweets, which limits its applicability to non-English-speaking regions and communities. Future research could address these limitations by expanding the dataset to include a broader range of social media platforms and incorporating multi-language sentiment analysis to gain a more comprehensive understanding of global public opinions. Further exploration of sector-specific sentiments could provide deeper insights into how AI is perceived across different industries, enabling more targeted policy responses. Expanding the focus to include the ethical implications of AI in employment and its impact on social equality would also be valuable avenues for future investigation.

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