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Sentiment Analysis on Job Descriptions in the Technology Sector: Measuring Positive and Negative Perceptions of Companies Using Natural Language Processing Techniques

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Abstract

Sentiment analysis in job descriptions plays a critical role in shaping employer branding and recruitment strategies. This study investigates the sentiment of job postings in the technology sector using NLP techniques, focusing on the emotional tone of descriptions across various job types, companies, and subcategories. The analysis reveals that positive sentiment predominates in job descriptions, with a clear trend towards using optimistic language to attract candidates. The findings show that Software Development positions tend to have the most positive tone, while roles such as IT Management exhibit a more balanced sentiment. Additionally, the use of inclusive language, such as "equal opportunity" and "years of experience", is prevalent in the descriptions, highlighting the growing importance of diversity and inclusivity in recruitment. Visualization tools like word clouds and trend analysis illustrate how sentiment shifts over time, with a noticeable increase in positive sentiment from 2020 onwards. The results underscore the potential of sentiment analysis and NLP in optimizing recruitment processes, aligning job descriptions with candidate expectations, and enhancing employer branding strategies.

Keywords: Sentiment Analysis, Job Descriptions, Technology Sector, Natural Language Processing, Employer Branding

1. Introduction

The importance of job descriptions in attracting talent has become increasingly recognized as organizations strive to refine their recruitment processes. Well-crafted job descriptions serve as a critical tool for aligning candidates' expectations with organizational needs, facilitating efficient recruitment. According to Kadri [1], Role-Wise Job Description Mapping offers substantial benefits by clearly delineating specific responsibilities and qualifications, which enhances candidate attraction and streamlines the hiring process. This approach ensures that potential candidates can easily assess whether their skills and aspirations match the job role. Deshmukh et al. [2] further emphasize the integration of effective job descriptions with advanced technology and analytics to optimize the candidate experience and enhance sourcing methods. The use of data-driven tools not only makes the recruitment process more efficient but also enables employers to reach a broader and more diverse pool of applicants. Alexander [3] highlights the significance of employer branding, reinforcing that compelling job descriptions positively influence how job seekers perceive a company, thereby attracting top talent. The strategic integration of employer branding within job descriptions plays a pivotal role in shaping the competitive landscape of talent acquisition. Together, these insights underscore the growing recognition of job descriptions as a central component of a competitive recruitment strategy in today's dynamic job market.

Job descriptions do more than just list qualifications and responsibilities; they also convey the company's culture and values, shaping candidates' perceptions of the work environment. Silva and Dias [4]found that when a company has a positive corporate reputation, coupled with well-crafted job descriptions, it significantly increases candidates'

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intentions to apply for positions. Anggoro and Harsono [5] argue that organizational reputation is crucial in influencing job application intentions, with employer branding serving as an important mediator. This highlights the need for organizations to craft job descriptions that accurately represent their values and organizational culture, as these descriptions are integral to engaging prospective employees. In an increasingly competitive job market, crafting compelling job descriptions that align with a company's brand can play a pivotal role in attracting the right candidates. Thus, job descriptions not only provide job details but also communicate important aspects of company culture, significantly influencing recruitment success.

Sentiment analysis has emerged as a key technique in assessing the emotional tone of job descriptions, enabling organizations to gauge how potential candidates perceive the roles being offered. This method, which uses Natural Language Processing (NLP), categorizes sentiments expressed in job descriptions into positive, neutral, or negative categories [6]. Sentiment analysis enables companies to derive insights into how job candidates might feel about the responsibilities described in the postings, as well as their potential fit within the company's work culture. Research by Jura et al. [7] shows that sentiment analysis can be applied to assess candidates' attitudes toward job environments and responsibilities, providing valuable data for recruitment strategies. Advanced methods, such as aspect-based sentiment analysis, can further dissect sentiment behind specific components of job descriptions, such as the company culture or compensation benefits. This deeper level of analysis helps organizations better understand candidate motivations and expectations, ultimately optimizing job descriptions to align with those preferences [6]. By incorporating sentiment analysis, companies can tailor their job postings to resonate more with potential candidates, improving the quality of applications and enhancing overall recruitment outcomes [7].

Despite the valuable insights provided by sentiment analysis, the influence of job descriptions on candidates' decision-making processes remains underexplored. Job descriptions serve as the first point of contact between potential employees and employers, offering detailed descriptions of job responsibilities and insights into company culture and values [8]. For some groups, such as disabled candidates, job descriptions may inadvertently appear less accommodating or misaligned with their skills [8]. Moreover, candidates interpret job descriptions as reflections of the actual workplace environment, where behaviors of current employees signal organizational characteristics [9]. However, a disconnect between what employers promote in job descriptions and the actual experiences of employees can lead to skepticism among job seekers, especially when they perceive a lack of authenticity or alignment with stated company values [10]. Addressing these issues can significantly enhance the effectiveness of job descriptions in shaping candidates' perceptions and improving hiring outcomes and employee satisfaction [11].

Another important issue in interpreting job descriptions, particularly in the technology sector, is the complexity and technicality of the language used, which can often alienate candidates who may not fully understand technical jargon. Reimer and Hamilton [12] highlight how the use of complex language and terminology in job postings, while reflective of technical requirements, can inadvertently introduce biases or reinforce gendered language, influencing candidate perceptions and application behavior. Research by Hu et al. [13] underscores how the nuances of language in job advertisements can perpetuate gender and racial segregation within the labor market, thus emphasizing the need for a nuanced understanding of word choice in job descriptions. Moreover, NLP techniques are increasingly used to analyze job postings and extract valuable trends and patterns. Studies utilizing NLP methods for classifying and analyzing job requirements, such as those by Lukauskas et al. [14] and Liu et al. [15], have demonstrated how sentiment analysis can reveal important language dynamics in job descriptions. However, the use of NLP must be accompanied by a conscious effort to ensure that language is emotionally resonant and inclusive, addressing potential biases and fostering engagement with marginalized groups [16].

Research demonstrates that sentiment analysis can provide valuable insights into how the language used in job descriptions is perceived. Misra and Gupta [17] discuss the broader application of sentiment analysis in social media research, but it is crucial to recognize that job descriptions, too, can be systematically analyzed for sentiment. This sentiment analysis technique provides a quantitative approach to evaluating the emotional tone of job postings. Abdullah and Rusli [18] explain that sentiment analysis quantifies sentiments expressed in written language by categorizing them into positive, negative, or neutral, allowing organizations to understand how candidates perceive their postings. Given that job postings in the tech sector often use technical jargon, sentiment analysis helps organizations determine how this language affects candidate attraction and engagement.

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In conclusion, the language used in job descriptions significantly impacts the recruitment process. Through sentiment analysis and NLP techniques, companies can gain valuable insights into how their job descriptions are perceived by potential candidates, ensuring that the language used aligns with both the company's values and the candidates' expectations. Crafting job descriptions with a focus on positive, inclusive, and clear language is essential for attracting the right talent, particularly in competitive sectors like technology. By addressing potential biases and negative cues, organizations can optimize their recruitment strategies, ensuring a diverse and qualified applicant pool while enhancing their employer brand.

2. Literature Review

Sentiment analysis is increasingly used in assessing job descriptions and recruitment processes, providing insights into job satisfaction and candidate preferences [7]. The language used in job advertisements plays a critical role in shaping candidates' perceptions and their fit with roles, which directly influences job attraction [19]. By integrating NLP techniques, organizations can more efficiently match resumes with job descriptions and streamline candidate screening, leading to better recruitment outcomes [20]. Additionally, crafting job ads with specific attributes that resonate with target populations can significantly impact candidates' application decisions [21], [22]. Ultimately, employing sentiment analysis and NLP helps optimize the recruitment process by aligning candidate expectations with employer values, improving hiring effectiveness.

Previous research has shown that the language used in job advertisements significantly impacts recruitment outcomes. Koçak et al. [23] found that the wording of personality requirements, particularly the use of behavioral phrasing, could increase job attraction across different age groups, highlighting the nuanced role of language in shaping job seeker perceptions. Krasna et al. [24] further emphasize that specific linguistic patterns are crucial for recruitment effectiveness, especially in targeting the right audience for various job roles. Additionally, the use of gendered language has been shown to affect women's likelihood of applying for leadership positions, with Reimer and Hamilton [12] noting that feminine language enhances application intentions among women with lower self-efficacy. This is supported by studies on gender bias, which suggest that the phrasing in advertisements can perpetuate stereotypes and influence the diversity of applicant pools [25]. Furthermore, the emphasis on inclusive language is increasingly recognized as essential in attracting a diverse talent pool, requiring employers to carefully consider linguistic choices to mitigate bias and enhance organizational attractiveness [26].

NLP plays a key role in sentiment analysis, particularly within Human Resources (HR) applications. By leveraging NLP techniques, organizations can automatically analyze sentiments expressed in job descriptions, performance reviews, and employee feedback, which helps enhance recruitment and retention strategies. Tanana et al. [27] highlight how NLP models can rate emotional content, benefiting organizations in understanding employee sentiments and improving workplace environments. NLP categorizes text into positive, negative, or neutral sentiments, aiding in gauging employee satisfaction and engagement [28]. Chaisen et al. [29] demonstrate that NLP can be used to analyze job postings, allowing organizations to tailor language that resonates with prospective applicants, making job descriptions more inclusive and appealing. Techniques like machine learning and lexicon-based approaches help organizations uncover insights into employee morale and organizational culture, streamlining sentiment analysis processes and empowering HR professionals to make data-driven decisions that improve recruitment outcomes [30].

Research has shown that sentiment in job descriptions varies across industries, with positive language playing a key role in attracting a diverse and qualified applicant pool. For instance, although Costello and Kim [31] focused on public sentiment regarding electric vehicles, their findings underscore the value of positive sentiment in technology-related communication, which influences candidates' perceptions. Similarly, Golz et al. [32] found that positive sentiments towards information technologies in healthcare settings, like psychiatric hospitals, enhance job satisfaction among healthcare professionals. This highlights the importance of language in job postings, especially in conveying the right attitudes to potential candidates.

On the other hand, negative sentiments, often related to job demands or required skills, can discourage applicants. This is particularly true in technology sectors, where overly technical jargon may alienate less experienced candidates. While positive discourse is common in technology sectors, negative sentiment about the complexity of roles can also prevail.

These findings suggest that sentiment in job descriptions is a crucial factor in recruitment effectiveness, particularly in the competitive technology sector. Crafting job descriptions with a focus on positive sentiment can help attract skilled talent and improve recruitment strategies.

3. Methodology

Figure 1 illustrates the overall flow of the sentiment analysis process, from data collection to the final sentiment analysis step.

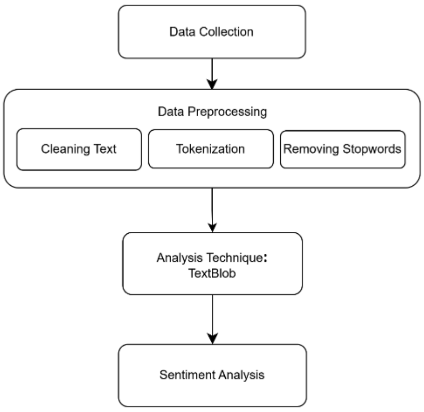

Figure 1. Research Methodology

3.1.Data Collection

The dataset used for this analysis contains job descriptions specifically from the technology sector. It includes various roles, such as software developers, IT support specialists, data scientists, and project managers. The dataset contains several key features that are valuable for sentiment analysis. These features are listed in the Table 1:

Table 1. Key Features of Technology Job Postings

Feature	Description
Job Title	The title of the job being advertised (e.g., Software Engineer, IT Manager).
Company	The company that posted the job.
Location	The geographical location of the job.
Job Type	Type of employment (e.g., full-time, part-time, contract, or temporary).
Job Function	The area of work the job pertains to (e.g., Development, Data Science, IT Support).
Description	The main body of the job description, detailing the roles, responsibilities, and qualifications.
Min and Max Salary	The salary range for the job, if provided. This can be useful for correlating sentiment with salary.
Is Remote	A flag indicating if the job is remote.
Date Posted	The date the job was posted.
Listing Type	Indicates if the listing is organic, sponsored, or part of a recruitment campaign.

These features are critical for sentiment analysis (understanding the tone of the job descriptions) and statistical analysis (exploring how factors like job type, company, or location influence sentiment). The dataset is sourced from Kaggle, a popular platform for data science competitions and learning that hosts a wide range of publicly available datasets, including job postings across various sectors. Specifically, this dataset contains job descriptions from the technology sector, making it ideal for performing sentiment analysis and exploring trends in the tech job market. Available for download and use by anyone, the dataset is curated and shared on Kaggle, which ensures it complies with the platform's ethical and legal standards for data usage, while also providing the necessary metadata for proper analysis.

3.2. Data Preprocessing

Preprocessing job descriptions for sentiment analysis involves a series of systematic steps to ensure the data is accurate and relevant. First, the text is cleaned by removing irrelevant entries, such as placeholders like "n/a," and eliminating special characters, numbers, and punctuation marks [33]. The text is then converted to lowercase to ensure uniformity, and any extra whitespace is removed. Next, tokenization breaks the text into individual units or tokens, allowing for easier analysis. Common words, known as stopwords (e.g., "the", "is", "and"), are removed as they do not add significant meaning to the analysis [20].

To further refine the text, techniques like stemming and lemmatization are applied to reduce words to their base or root form, with lemmatization being preferred for its accuracy. Additionally, URLs and email addresses are removed, as they do not provide valuable insights for sentiment analysis. The dataset is also checked for missing or null descriptions, which are eliminated to maintain data integrity.

For deeper analysis, text mining techniques are used to extract key skills and requirements from job descriptions [34], while natural language processing (NLP) methods enhance the identification of relevant data features [35]. Advanced methods, such as latent feature analysis, can be employed to uncover underlying attributes within the job descriptions [36]. Finally, the text is often converted into numerical representations through techniques like word embeddings, TF-IDF vectorization, or the bag-of-words model, depending on the specific requirements of the analysis. This comprehensive preprocessing approach ensures that the data is cleaned, standardized, and ready for sentiment analysis, enabling effective interpretation of job market trends.

3.3. Sentiment Analysis Technique

Sentiment analysis tools such as TextBlob and VADER are widely used for analyzing the emotional tone of textual data. TextBlob calculates sentiment by assigning a polarity score, which ranges from -1 (indicating negative sentiment) to 1 (indicating positive sentiment). The polarity score is computed using the formula:

$$Polarity = \frac{Sum\ of\ Sentiment\ Scores\ of\ Words\ in\ Text}{Number\ of\ Words\ in\ Text} \tag{1}$$

This formula averages the sentiment scores of individual words to provide an overall sentiment for the text. Additionally, TextBlob computes a subjectivity score, ranging from 0 (objective) to 1 (subjective), which measures how opinionated or factual the text is. In contrast, VADER (Valence Aware Dictionary and sEntiment Reasoner) is specifically designed for analyzing informal text such as social media posts. VADER calculates sentiment using a lexicon of sentiment-associated words, adjusting the scores based on intensity modifiers like capitalization, punctuation, and negations. For example, words in all caps or with excessive exclamation marks receive a higher intensity score. The overall compound score in VADER is computed using the following formula:

$$Compound\ Score = \frac{\sum Sentiment\ Scores}{\sqrt{\sum(Sentiment\ Scores)^2}} \tag{2}$$

This formula normalizes the sentiment scores and combines them into a single value that ranges from -1 (most negative) to 1 (most positive). Based on this compound score, VADER classifies sentiment as positive (if the score is greater than 0.05), negative (if the score is less than -0.05), and neutral (if the score is between -0.05 and 0.05). While TextBlob works well for general text analysis and is useful for structured content, VADER excels in analyzing informal, social media-based text, where intensity and contextual factors play a significant role. Both tools provide a robust framework for analyzing sentiment, making them suitable for applications like sentiment analysis in job descriptions, social media posts, or customer reviews.

3.4.Analysis

To interpret the sentiment data and explore trends, various statistical techniques are employed. Descriptive statistics such as the mean and median sentiment scores are calculated to summarize the overall sentiment distribution across different categories, helping to identify the central tendency of sentiment in job descriptions for each group. The chi-square test is used to determine whether there is a statistically significant difference in the sentiment distribution between categories such as job types or companies. For instance, it can test if the sentiment distribution of job descriptions differs significantly between remote and non-remote job types. The ANOVA (Analysis of Variance) technique is also used to compare the mean sentiment scores across multiple groups, such as different job roles or subcategories, to see if certain roles like software developers or IT managers tend to have more positive or negative descriptions. Visualizations, including countplots, pie charts, and line plots, are used to display the sentiment distribution and trends over time. For example, a line plot can show sentiment trends over months or years, highlighting

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whether companies have become more positive or negative in their job descriptions over time. The combination of TextBlob for sentiment analysis and these statistical techniques allows for a comprehensive understanding of sentiment across different companies, roles, and job types, providing valuable insights into how job descriptions are perceived in the technology sector.

4. Results and Discussion

4.1. Result

The sentiment distribution of job descriptions in the technology sector is depicted in Figure 2. As shown, the majority of job descriptions are classified as positive, with a significantly larger number of positive sentiment descriptions compared to neutral or negative ones. The distribution highlights an overwhelming prevalence of positive language in the job descriptions, which may indicate that companies in the technology sector tend to emphasize the appealing aspects of their roles and organizational culture. In contrast, the number of neutral and negative job descriptions is considerably lower, suggesting that companies may avoid using overly negative or neutral tones in their job listings. This trend is useful for understanding how sentiment is distributed across job postings, offering insights into employer branding and how they communicate with potential candidates.

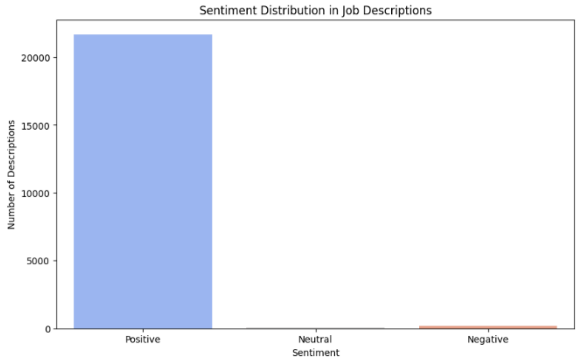

Figure 2. Sentiment Distribution in Job Descriptions

The chart presented in Figure 3 shows the sentiment distribution across different job types within the dataset. It visualizes the number of job descriptions categorized as positive, neutral, or negative based on the sentiment analysis of their content. The job types are color-coded in the legend, with categories such as full-time, internship, contract, and part-time prominently represented. The chart indicates that full-time positions have the highest number of job descriptions, with a significant portion classified as positive. Other job types, such as internship and part-time positions, also display a variety of sentiments but in lower frequencies compared to full-time roles. This distribution provides valuable insights into how sentiment varies across different types of employment, revealing trends in how companies present various job roles and their associated emotional tones. The chart emphasizes that most job descriptions, regardless of job type, tend to be more positive, which could reflect the companies' effort to attract potential candidates by showcasing an optimistic view of the roles.

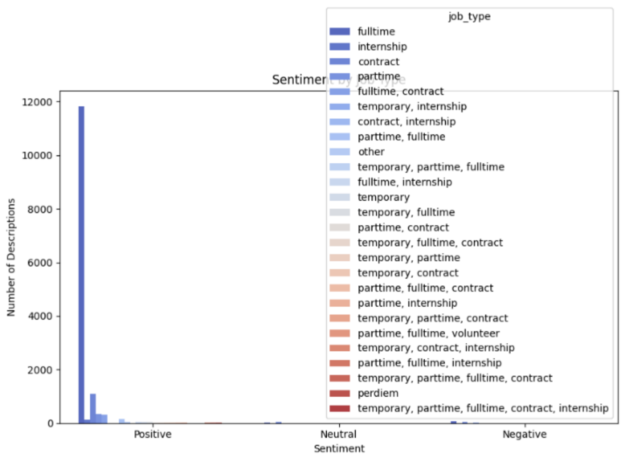

Figure 3. Sentiment Distribution by Job Type

The chart in Figure 4 shows a comparison of sentiment across different job subcategories within the technology sector. It visualizes the sentiment distribution of job descriptions categorized into three subcategories: Software Development, IT Management, and Others. As observed, Software Development job descriptions exhibit a predominantly positive sentiment, with a significantly higher number of positive descriptions compared to the other categories. IT Management job descriptions also show a positive sentiment but to a lesser extent, with more balanced sentiment between positive and neutral categories. The Others category, which likely includes various other job functions, has a more evenly distributed sentiment, although the number of descriptions is notably lower compared to the other two categories. This distribution provides insights into how job descriptions are framed emotionally across different roles in the technology sector, indicating that roles like Software Development tend to have more optimistic and appealing job postings.

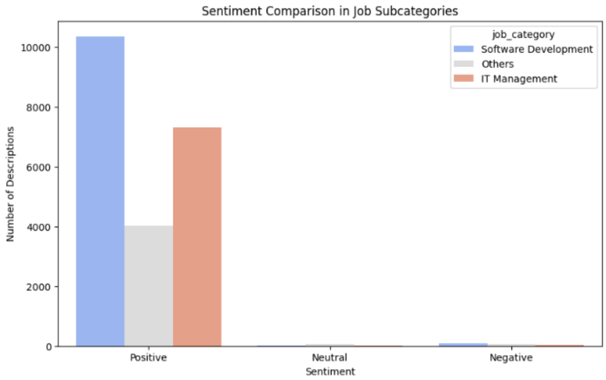

Figure 4. Sentiment Comparison in Job Subcategories

The line chart shown in Figure 5 illustrates the sentiment trends in job descriptions over time, from the year 1999 to 2024. The chart tracks the number of job descriptions classified as positive, neutral, or negative for each month. Notably, the chart shows a sharp increase in job descriptions starting from around 2020, with a significant dominance of positive sentiment (indicated by the green line). The number of negative and neutral descriptions remains relatively low throughout the time period, with positive sentiment consistently outweighing the others, especially in recent years. This trend suggests that over time, companies have increasingly focused on presenting job descriptions with a more optimistic tone, particularly in the last few years. The chart provides valuable insights into how the tone of job descriptions in the technology sector has evolved, reflecting the shifting dynamics of employer branding and communication strategies.

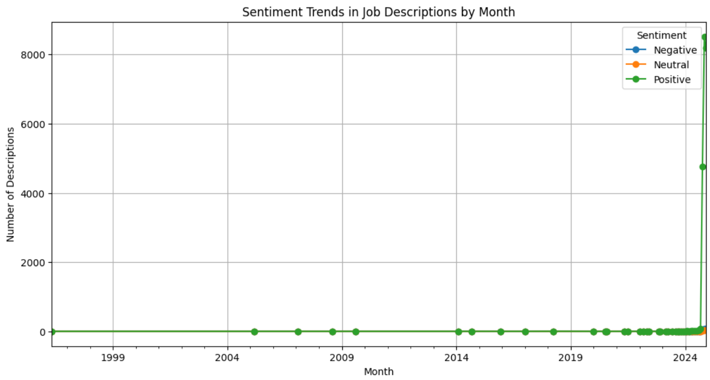

Figure 5. Sentiment Trends in Job Descriptions by Month

Figure 6. word cloud of job descriptions visualizes the most frequent terms used across job descriptions in the technology sector, with the size of each word representing its frequency. Prominent terms such as "years of experience", "full-time", "equal opportunity", and "national origin" appear larger, indicating their frequent use in the descriptions. The word cloud reveals that companies in the technology sector emphasize experience, teamwork, and skills, as well as promoting equal opportunity employment. Phrases like "sexual orientation" and "race color" suggest that inclusivity and non-discrimination are important values highlighted in these job postings. Overall, this word cloud provides a snapshot of the key themes and language commonly used by employers in the sector.

Figure 6. Word Cloud of Job Descriptions

4.2. Discussion

The sentiment analysis of job descriptions in the technology sector reveals several interesting insights that align with findings from previous research on the influence of language in job advertisements. Figure 2 highlights the overwhelming prevalence of positive sentiment across job descriptions, with a significantly higher number of positive job postings compared to neutral or negative ones. This trend is consistent with the broader theme in recruitment literature, where the emotional tone of job descriptions has been shown to impact applicants' perceptions and their likelihood of applying. As indicated by Jura et al. [7], sentiment analysis can provide insights into job satisfaction, though further studies are needed to connect sentiment directly to specific outcomes like job satisfaction in particular professional sectors.

Furthermore, Figure 3 and Figure 4 reveal sentiment differences across various job types and subcategories such as Software Development and IT Management. Similar to the findings by Zhou et al. [37], the sentiment in job descriptions varies by job role, with Software Development positions showing a stronger positive sentiment, likely reflecting the industry's emphasis on growth, innovation, and opportunity. IT Management, on the other hand, exhibited more balanced sentiments, which may reflect the demanding nature of managerial roles and the need for a more neutral or objective tone in job descriptions. This finding corroborates earlier work by Petry et al. [19], which suggests that job characteristics, including the tone of job descriptions, directly influence candidates' perceptions of their potential fit with a job.

Additionally, the pie chart in Figure 5 underscores the prevalence of positive sentiment, reinforcing the notion that companies, particularly in the technology sector, prioritize optimistic language to attract potential candidates. This aligns with the research by Chaturvedi et al. [38], who highlight the importance of using inclusive language that appeals to a diverse candidate pool, as the positive tone in job descriptions is essential for promoting employer branding and attracting high-quality applicants.

The word cloud visualization in Figure 6 offers another layer of insight, showing frequent terms like "years of experience," "full-time," and "equal opportunity". These terms reflect key themes often emphasized in job descriptions, aligning with Mahjoub and Kruyen [21], who argue that inclusive language and clarity in describing employment conditions significantly affect candidates' decisions to apply. The frequent use of terms related to equal opportunity and sexual orientation indicates the growing importance of inclusivity in the recruitment process, which is becoming a central aspect of modern recruitment strategies.

The trend analysis in Figure 5 further reveals a dramatic increase in job descriptions starting in 2020, with positive sentiment continuing to dominate, which may reflect a broader shift in the industry towards presenting more attractive, inclusive, and optimistic portrayals of job roles. The increase in positive language aligns with findings from Costello and Kim [31], who suggest that positive sentiment in job postings can attract a broader, more qualified applicant pool. Moreover, it indicates the evolving role of NLP and sentiment analysis in improving recruitment processes and aligning candidate expectations with employer values.

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The findings from this analysis also align with research indicating that negative sentiment in job descriptions can deter applicants, especially when the descriptions use overly technical or demanding language. This is consistent with Akbari et al. [39], who note that negative sentiments in specific industries, such as the technology sector, can create barriers for less experienced candidates. Therefore, crafting job descriptions with a focus on positive sentiment, as seen in the majority of job postings in this study, can help organizations improve their recruitment strategies, particularly in highly competitive sectors like technology.

In conclusion, the results of this sentiment analysis offer valuable insights into the emotional tone of job descriptions in the technology sector. By utilizing sentiment analysis and NLP techniques, companies can optimize their recruitment strategies, ensuring that their job descriptions align with the expectations and values of prospective candidates. Moreover, focusing on positive sentiment and inclusive language can enhance employer branding, attract diverse talent, and ultimately improve recruitment outcomes.

5. Conclusion

This study employed sentiment analysis to examine job descriptions within the technology sector, revealing valuable insights into how companies communicate with potential candidates through the emotional tone of their job postings. The findings indicate that the majority of job descriptions exhibit a positive sentiment, with companies predominantly using optimistic language to attract top talent. Sentiment analysis of job types, companies, and job subcategories revealed that roles such as Software Development tend to have a more positive tone compared to other roles, such as IT Management, which showed a more balanced sentiment. These results align with previous research, highlighting the importance of language in recruitment and employer branding. The visualizations, including pie charts, line charts, and the word cloud, further emphasized the focus on inclusive language, such as "equal opportunity" and "years of experience", reflecting trends in the technology sector’s recruitment practices. Overall, the study demonstrates how sentiment analysis, supported by Natural Language Processing (NLP) techniques, can optimize recruitment strategies by providing deeper insights into the emotional tone of job descriptions, allowing companies to better align their messaging with candidate expectations.

6. Declarations

6.1. Author Contributions

Conceptualization: L.Y., M.P.; Methodology: L.Y., M.P.; Software: L.Y.; Validation: M.P.; Formal Analysis: L.Y.; Investigation: L.Y.; Resources: M.P.; Data Curation: L.Y.; Writing – Original Draft Preparation: L.Y.; Writing – Review and Editing: M.P.; Visualization: L.Y.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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