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Applying K-Means Clustering to Group Jobs Based on Location and Experience Level: Analysis of the Job Recommendation

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Abstract

Labor market analysis plays a crucial role in helping job seekers identify employment opportunities that align with their qualifications, location, and experience level. This study uses the K-Means clustering algorithm to group jobs based on these critical factors. By analyzing job market data, the research identifies the most sought-after skills across various industries and highlights the geographic and experience-level disparities in job availability. Key findings include the high demand for foundational skills such as customer service, sales, and production planning, as well as more specialized skills like Medical Research in certain sectors. The study provides actionable insights for job seekers and policymakers, suggesting that targeted skill development and training programs are essential for improving job match quality. However, the study also acknowledges its limitations, such as the lack of consideration for broader economic and social factors that influence labor market trends. Future research is recommended to address these gaps, using more comprehensive datasets and advanced analytical techniques.

Keywords: K-Means Clustering, Job Market Analysis, Skill Demand, Job Search, Labor Market Trends

1. Introduction

The Labor market analysis plays a critical role in improving job seekers' ability to find suitable employment that aligns with their skills, location, and experience levels. With the integration of machine learning technologies, the landscape of job searching has dramatically transformed, enabling more efficient and tailored job recommendations. Machine learning algorithms can analyze vast amounts of data from online job portals to optimize the matching process between job postings and candidates' profiles. This enhances the overall efficiency of the job search process by helping individuals find jobs that are a better fit for their qualifications [1].

Furthermore, machine learning facilitates personalized job recommendations, which can help job seekers navigate various barriers, including economic challenges and mental health concerns [2]. This technology analyzes job market data to identify patterns, ultimately providing job seekers with insights tailored to their personal circumstances. By leveraging these insights, machine learning can boost self-efficacy and motivation, helping individuals persist in their job search, which is particularly valuable in difficult economic times or amid challenges such as the COVID-19 pandemic [3].

Job searching, however, remains a complex process due to several challenges, primarily driven by the uneven distribution of job opportunities across geographic regions. There are substantial disparities in employment rates between regions, where some may experience high unemployment, while others face labor shortages. This imbalance complicates the job search process for individuals in economically disadvantaged areas, where job availability is often limited. These challenges are further exacerbated by inconsistent job requirements, with some positions demanding specific skills and experience levels that applicants may not possess, thus making the process even more difficult for certain groups [4], [5], [6]. In addition to these challenges, psychological factors such as self-efficacy and motivation significantly influence job seekers' behaviors and persistence in their search [7]. Individuals with higher levels of

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psychological capital tend to set more ambitious goals and are more likely to persist through setbacks in the job search process. Addressing these psychological barriers through machine learning technologies could enhance the job matching process by aligning candidates’ skills and experiences with the most relevant job opportunities, thus improving the overall search experience [8]. The ability of machine learning algorithms to offer personalized recommendations can provide an effective solution to these challenges by better matching job seekers with opportunities that fit their qualifications and geographical preferences.

Grouping jobs based on location and experience level represents a significant challenge in the labor market. Geographic disparities in job availability often led to mismatches between candidates' locations and the available job opportunities. For instance, some regions may have a higher concentration of job openings, while others may face higher unemployment rates. This disparity necessitates effective resource allocation strategies to facilitate job mobility and accessibility, which is crucial for better aligning job seekers with opportunities [9]. In addition to geographical challenges, varying experience requirements for different job roles further complicate the job search. Many positions require extensive expertise, which puts inexperienced job seekers at a disadvantage. Additionally, job seekers from specific backgrounds such as migrants or individuals with lower levels of education may struggle to find suitable positions due to their skill set or the local labor market conditions [10].

Machine learning can address these issues by grouping job listings based on both location and experience level, which helps to improve the job matching process. By incorporating algorithms that can account for these factors, such as K-Means clustering, job seekers can receive recommendations that are better aligned with their qualifications and preferred job locations. This approach can significantly enhance the prospects for job seekers, helping them identify opportunities that they might have otherwise missed due to geographical or experience-related barriers.

The psychological aspects of the job search process, such as motivation and self-efficacy, play an important role in a job seeker's persistence. Studies have shown that individuals with higher psychological capital tend to set more ambitious goals and engage more actively in their job search process [7]. Machine learning can further enhance this process by providing personalized insights and job recommendations that match job seekers' qualifications, location preferences, and experience levels. Such a system could allow job seekers to locate positions that better suit their qualifications and aspirations, boosting their chances of success in finding suitable employment [11].

This study focuses on grouping jobs based on two key factors: location and experience level, by utilizing the K-Means Clustering algorithm. K-Means is a widely used method for categorizing data points based on their features, making it particularly effective for grouping job listings in a context where geographical location and experience levels are critical factors. By using K-Means clustering, this research aims to provide job seekers with clearer insights into job opportunities that match their qualifications and preferred locations, streamlining the job search process. This approach allows for the identification of patterns in job market data, which helps job seekers understand where their skills are most in demand [12]. The application of this methodology not only benefits job seekers but also informs workforce development strategies by identifying in-demand skills across different regions [13].

The primary objective of this research is to leverage the K-Means Clustering algorithm to group jobs based on location and experience level. This approach offers actionable recommendations and insights into job market patterns across different regions, enabling job seekers to navigate opportunities more effectively. By analyzing job listings in this way, we can identify job clusters that align with specific experience requirements, making it easier for job seekers to find positions that are well-suited to their qualifications [14]. This research also explores how geographic disparities and varying experience levels can complicate the job search, and how the K-Means algorithm can help clarify these complexities.

The impact of this research is to provide job seekers with a tool that enhances their ability to find jobs that align with their experience and location preferences. By utilizing the K-Means Clustering algorithm, this study helps to identify job patterns and trends, enabling job seekers to focus on the most relevant job opportunities. This approach significantly streamlines the job search process by helping job seekers find positions that match their qualifications within specific geographical areas. As a result, job seekers will have improved access to job opportunities that are better tailored to their skill sets, experience, and location preferences, which can ultimately lead to higher job satisfaction and reduced search time [6].

Additionally, the implementation of K-Means clustering has significant implications for employers. By analyzing job postings and the preferences of job seekers, employers can better understand market trends and patterns, allowing them to adjust their recruitment strategies accordingly. This data-driven approach helps employers improve their job listings, ensuring they attract the right talent by providing clearer expectations related to experience requirements and job locations. As companies leverage these insights, they can streamline their hiring processes, resulting in more effective recruitment and higher-quality candidates [15]. Moreover, the use of recommendation algorithms enhances the overall recruitment process by offering job seekers tailored job suggestions, improving engagement and satisfaction among potential applicants [16]. The integration of K-Means clustering in the job market analysis can foster a more efficient labor market by aligning job seekers' skills and preferences with employers' needs, benefiting both parties and contributing to the overall economy [17].

2. Literature Review

Clustering analysis has gained significant attention in labor market studies, offering valuable insights into the relationships between employment types, job quality, and socioeconomic factors. This approach helps uncover patterns in the labor market, shedding light on aspects like health outcomes, wage levels, and job satisfaction. It allows researchers to better understand employment dynamics and how various factors shape the workforce.

A key contribution comes from Ketels and Protsiv [18], who explored the relationship between industry clusters and economic performance. They found that clusters of related industries can enhance wages and job creation. By viewing clusters as interconnected networks rather than isolated sectors, researchers can better understand how collaboration within industries fosters economic prosperity. This approach emphasizes the importance of analyzing industries within broader economic contexts to interpret labor market trends effectively.

Additionally, clustering techniques have been used to explore employment quality and its impact on health. Eisenberg-Guyot et al. [19] examined how employment quality affects health, particularly across gender. Their findings show that women are often relegated to lower-wage clusters, which negatively impacts their health. This highlights the need for tailored interventions to address challenges faced by different demographic groups in the labor market, especially regarding employment quality for women and marginalized communities.

Job satisfaction is another area where clustering has proven valuable. Thụ et al. [20] found that grouping employees by satisfaction levels can provide insights into performance variations. Their research suggests that understanding these clusters can help optimize workplace conditions, improving job satisfaction. Similarly, Jonsson et al. [21] showed that poor-quality jobs are linked to mental health issues, further emphasizing how clustering can provide insights into employment's impact on well-being.

In labor market studies, latent class analysis (LCA) has been used to develop typologies that reflect the risk of mental health disorders related to job quality. Gevaert et al. [22] found that precarious employment correlates with poor health outcomes, showing how clustering can enhance understanding of employment as a determinant of health. This highlights the broader role of employment quality in shaping public health.

The versatility of K-Means clustering extends beyond labor markets. In marketing, Chen [23] discusses how K-Means can segment customers based on purchasing behavior, helping businesses understand consumer trends and tailor their offerings. This segmentation is vital for targeted marketing strategies, as shown by Tabianan et al. [24]. In energy systems, Miraftabzadeh et al. [25] utilized K-Means for applications like load forecasting and condition monitoring, demonstrating its utility in data-driven decision-making.

In labor market research, K-Means clustering helps identify job patterns based on factors like location and experience. Aloshyna and Kozenkov [26] used clustering to assess labor supply and demand in Ukraine, revealing how social, economic, and legal factors affect regional disparities. This approach can inform policies aimed at balancing labor supply and demand. Lu et al. [27] extended clustering to job advertisements in China, identifying segments related to salary and labor market characteristics. Their study shows that clustering can capture the multidimensional nature of labor market segmentation, which single-dimensional analyses often miss. This insight underscores the importance of clustering in understanding labor market complexities.

Boldis et al. [28] applied clustering to study labor market attachments of women with Polycystic Ovary Syndrome (PCOS), uncovering how health factors influence employment challenges. This demonstrates how clustering can link health and social factors to labor market trends, providing insights for policy improvements. Finally, König [29] examined industrial clusters and their impact on labor market competition and collaboration. He found that firms in similar industries share labor pools, influencing hiring practices. This emphasizes how clustering methodologies help understand how industry-specific dynamics affect employment.

In conclusion, clustering methodologies, especially K-Means clustering, are essential tools for analyzing labor market dynamics. They help uncover patterns related to employment quality, wages, and job satisfaction, providing insights that can inform policies aimed at improving labor market efficiency and well-being. The versatility of clustering in fields like marketing, energy systems, and inventory management also highlights its broad applicability. As the labor market continues to evolve, clustering methods will remain a valuable tool in understanding and addressing its complexities.

3. Methodology

The diagram presented in Figure 1 illustrates the methodology used in this study, which consists of four main steps: data collection, data preprocessing, the application of the clustering algorithm, and the final clustering analysis. Each step is essential for ensuring that the data is properly prepared and analyzed to derive meaningful results.

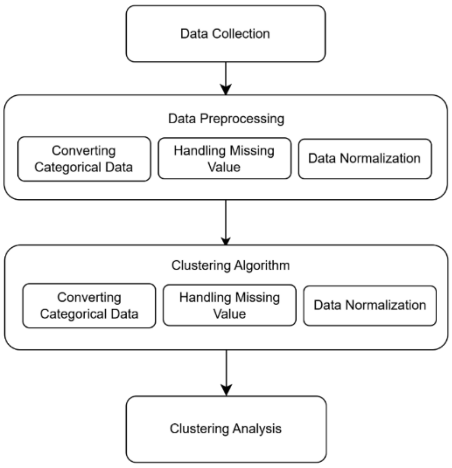

Figure 1. Research Methodology

3.1.Data Collection

Data collection is the initial phase in any data analysis process. In this case, the data is gathered from Kaggle, a renowned platform for machine learning datasets, which provides publicly available datasets shared by individuals, organizations, or researchers. These datasets cover a wide range of domains, including finance, healthcare, education, and job market analysis, making them an excellent resource for various research topics.

The dataset includes several important features related to job recommendations, which are essential for clustering jobs based on location and experience level. These features include job title, location, experience level, required skills, industry, salary, employment type, and company. Table 1 summarizes the key features included in the dataset, providing a clear overview of the information used for clustering analysis.

Table 1. Features in the Job Recommendation Dataset

Feature	Description
Job Title	The name of the position or role being offered (e.g., "Software Engineer").
Location	The geographical area where the job is based (e.g., "New York", "San Francisco").
Experience Level	The required experience level for the job (e.g., "Entry-level", "Mid-level", "Senior").
Required Skills	A list of skills needed for the job, such as programming languages, data analysis, etc.
Industry	The industry sector of the job (e.g., "Technology", "Healthcare", "Finance").
Salary	The salary range or amount offered for the job (e.g., "$60,000 - $80,000").
Job Description	A brief description of the job role and responsibilities (if available).

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Employment Type	The type of employment (e.g., "Full-time", "Part-time", "Freelance").
Company	The name of the company offering the job (e.g., "Google", "Microsoft").

3.2. Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset for clustering analysis, as it ensures that the data is clean, consistent, and in a suitable format for machine learning algorithms. In this process, categorical data, such as location and experience level, must be converted into numerical formats. For categorical variables with a natural order, such as experience level, Label Encoding is applied, where each unique category is assigned an integer value. On the other hand, for categorical variables without any inherent order, such as location, One-Hot Encoding is used. This technique creates binary columns for each category, allowing the model to handle these variables effectively.

Additionally, missing values in the dataset must be addressed to ensure that the machine learning model is not biased or affected by incomplete data. Missing values in categorical columns, such as location or experience level, are imputed by replacing them with the most frequent category (mode), while numerical columns are imputed with the mean or median, depending on the distribution of the data.

Finally, normalization or scaling of the data is an important step, especially when using algorithms like K-Means clustering, which are sensitive to the scale of features. Variables with different scales can disproportionately influence the clustering process. Therefore, all numerical features are normalized, ensuring they are on the same scale and preventing any single feature from dominating the clustering process. By transforming the data into a standardized format, we ensure that the clustering model operates effectively and yields meaningful insights.

3.3. Cluster Algorithm

The K-Means Clustering algorithm follows an iterative process to assign data points to clusters and refine the cluster centers. The process continues until the centroids no longer change significantly, ensuring that the clustering is stable. Table 2 summarizes the key steps involved in the iterative process of K-Means clustering.

Table 2. Iterative Process of K-Means Clustering

Step	Description
Initialization	Select the number of clusters (**K**) and randomly initialize the cluster centroids.
Assignment Step	Assign each data point to the nearest centroid based on a distance metric (e.g., Euclidean distance).
Update Step	Recalculate the centroids by finding the mean of all the points assigned to each cluster.
Convergence	Repeat the assignment and update steps until the centroids no longer change significantly or a predefined number of iterations is reached.

To determine the optimal number of clusters (K) for the K-Means clustering algorithm, two common methods are used: the Elbow Method and the Silhouette Score. The Elbow Method involves running the K-Means algorithm for different values of K and plotting the Within-Cluster Sum of Squares (WCSS) for each value of K. The WCSS measures the compactness of the clusters, and the goal is to minimize it. The optimal value of K is identified at the point where the rate of decrease in WCSS slows down significantly, forming an "elbow" in the graph. This elbow indicates the point beyond which adding more clusters does not significantly improve the clustering result.

The Silhouette Score is a metric used to evaluate the quality of the clusters formed by the K-Means algorithm. It measures how similar each point is to its own cluster compared to other clusters. A higher Silhouette Score indicates that the data points are well-clustered and have distinct boundaries from other clusters. Table 3 outlines the interpretation of the Silhouette Score and its significance in determining the quality of clustering.

Table 3. Interpretation of Silhouette Score

Silhouette Score Range	Interpretation
1	Perfect clustering; the data points are well-separated and very cohesive.
0	The data points are on or near the boundary between clusters.
-1	Poor clustering; the data points are likely assigned to the wrong cluster.

4. Results and Discussion

4.1. Result

Figure 2 illustrates the top skills required across various industries, showcasing the frequency of these skills in job postings. The x-axis represents the frequency of each skill, while the y-axis lists the specific skills. Skills like Teaching, Research, and Sales are in high demand, with the highest frequencies, indicating that these skills are widely sought after across different industries. On the other hand, skills such as Medical Research, Patient Care, and Pharmaceuticals appear less frequently, suggesting that these are more specialized skills with more specific demands. This figure provides valuable insight into the skills that are most critical in today's labor market, which is essential for understanding how job seekers' qualifications align with job requirements based on location and experience level.

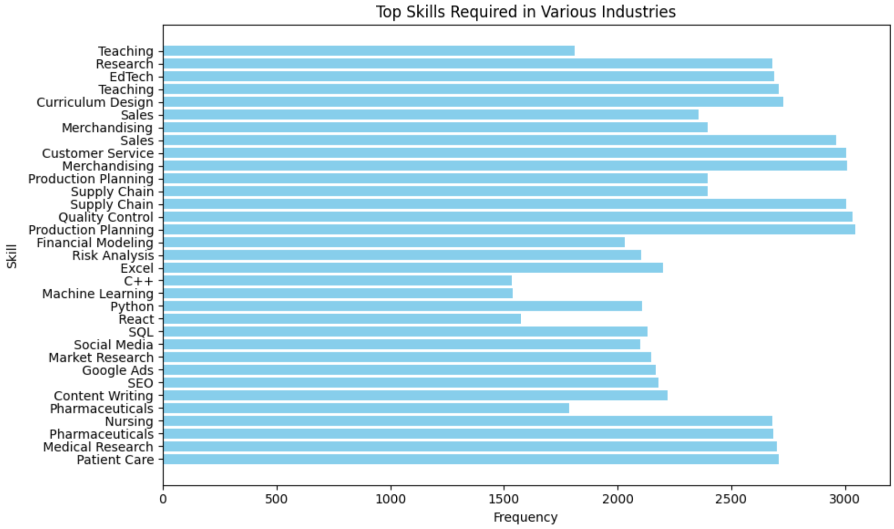

Figure 2. Top Skills Required in Various Industries

Figure 3 presents a word cloud depicting the top skills required across various industries. In this visualization, the size of each word corresponds to its frequency, with larger words representing skills that are more frequently mentioned in job postings. The most prominent skills, such as Customer Service, Patient Care, Supply Chain, Medical Research, and Production Planning, appear in larger fonts, signifying their high demand across industries. Conversely, less frequently mentioned skills such as Market Research, Quality Control, and Curriculum Design are represented in smaller text, indicating their more specialized or less common requirement. This word cloud reinforces the findings from Figure 2, highlighting the essential skills sought by employers, with certain skills like Customer Service and Supply Chain being notably more in demand across various sectors.

Figure 3. Word Cloud of Top Skills Required

Figure 4 displays a heatmap representing the top skills required across various industries. The x-axis lists the skills, while the y-axis represents different industries. The color intensity indicates the frequency of each skill in job postings across the respective industries, with darker shades of blue reflecting higher frequencies. Skills such as Production

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Planning, Customer Service, and Medical Research appear prominently in several industries, as evidenced by the darker blue shades. This suggests that these skills are highly in demand across multiple sectors. On the other hand, skills like Content Writing and Financial Modeling have lighter shades, indicating they are less frequently required across these industries. This heatmap provides a clear visual representation of skill demand across various industries, helping to highlight which skills are essential for job seekers in specific fields

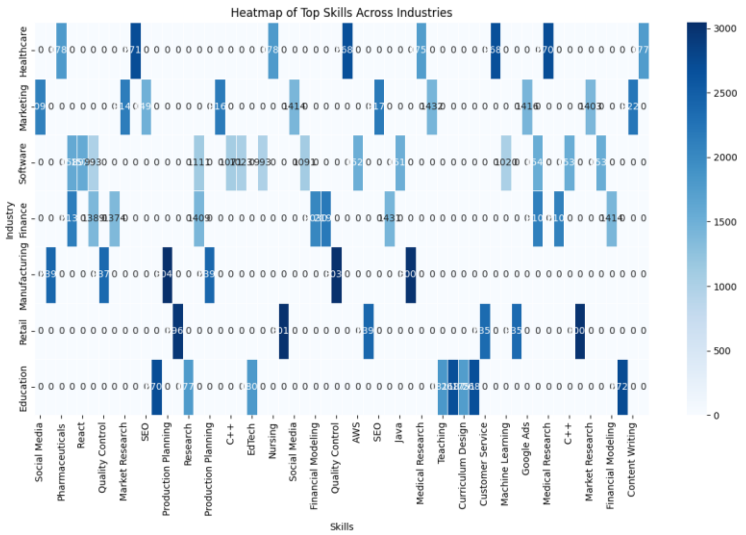

Figure 4. Heatmap of Top Skills Across Industries

Figure 5 shows a stacked bar chart representing the distribution of top skills required across various industries. The x-axis displays the industries, and the y-axis represents the frequency of each skill within those industries. Each color in the stacked bars corresponds to a different skill, as indicated in the legend on the left. From the chart, we can observe that skills like Teaching, Supply Chain, and Customer Service are consistently required across multiple industries, as evidenced by the broad color bands in several stacked bars. On the other hand, skills such as Machine Learning and Financial Modeling appear more concentrated in specific sectors like Software and Finance, respectively. This visualization complements the data presented in Figure 4, providing a clear overview of how skills are distributed and required across different sectors.

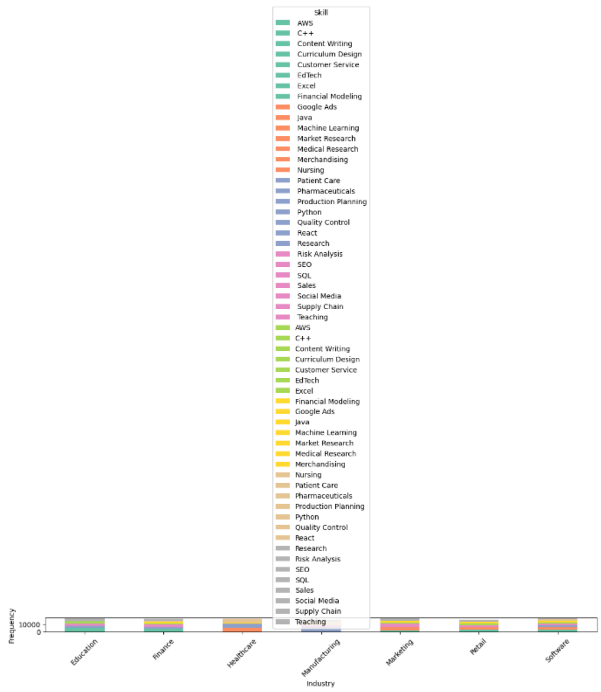

Figure 5. Stacked Bar Chart of Top Skills Across Industries

Figure 6 presents a radar chart that visualizes the distribution of top skills in a selected industry. Each axis of the chart represents a different skill, and the shape of the polygon shows how each skill is valued within the industry. The larger the area covered by the polygon, the higher the demand for those specific skills in that industry. This chart allows for a quick comparison of the relative importance of various skills within a particular sector, helping to identify which skills are prioritized and how they stand in relation to each other. The skills shown in the radar chart could include those such as Customer Service, Supply Chain, and Market Research, depending on the selected industry.

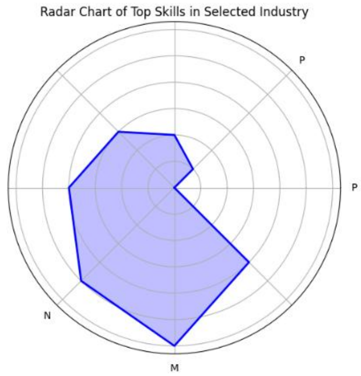

Figure 6. Radar Chart of Top Skills in Selected Industry

Figure 7 displays a treemap of skills across various industries. Each block in the treemap represents a specific skill, with the size of the block corresponding to the frequency or demand for that skill in a particular industry. The blocks are color-coded to indicate which industry the skill is most relevant to, such as Healthcare, Retail, Finance, and Education. For example, skills like Medical Research and Nursing are prominently placed within the Healthcare industry, while Sales and Customer Service are dominant in the Retail industry. This visual format helps to quickly identify which skills are in demand in each sector and shows the distribution of skills across industries.

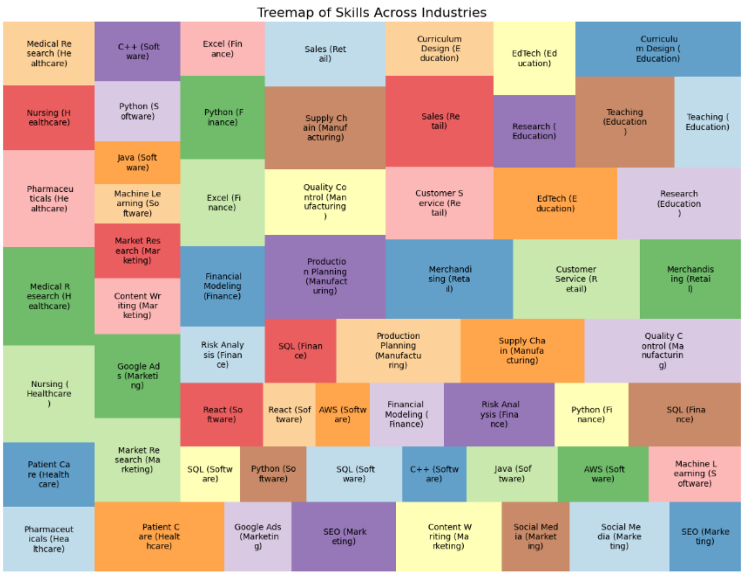

Figure 7. Treemap of Skills Across Industries

4.2. Discussion

The results provide a clear picture of the most in-demand skills across various industries. Skills such as Teaching, Research, and Sales show high demand, suggesting that these competencies are essential across multiple sectors. These findings align with the research by Ketels and Protsiv [18], which emphasized that clusters of related industries can contribute to higher wages and job creation. In this context, foundational skills like teaching and research are integral to fostering economic growth and efficiency in the labor market.

Additionally, there is a noticeable distinction between skills in high demand, such as Customer Service, Patient Care, and Supply Chain, and more specialized skills, such as Market Research and Curriculum Design, which are less frequently required. This pattern is consistent with Gevaert et al. [22], who highlighted that specialized skills tend to have lower demand but remain important in specific sectors. This observation underscores the need for targeted skill development, especially for niche areas that, despite their lower frequency of demand, are vital in certain industries.

Certain skills, such as Production Planning, Customer Service, and Medical Research, are essential across multiple industries, signaling that these competencies are critical in driving job growth and sectoral development. This aligns with Jonsson et al. [21], who linked job quality and mental health, suggesting that job satisfaction and well-being are closely tied to the demand for specific skills.

Moreover, some skills like Teaching, Supply Chain, and Customer Service remain consistently in demand across various industries, highlighting their broad applicability and relevance in diverse job markets. However, more technical and specialized skills, such as Machine Learning and Financial Modeling, are concentrated in specific sectors like Software and Finance, which points to the importance of aligning one's skill set with sector-specific demands.

The analysis also reveals the varying degrees of skill demand across industries, helping both job seekers and employers understand which skills are prioritized in different fields. For example, those with expertise in Medical Research may focus their job search within the Healthcare or Pharmaceutical sectors, where this specialized skill is more sought after.

These findings have significant implications for both policymakers and job seekers. For policymakers, the data suggests that training and development programs should focus on cultivating the most in-demand skills, such as Customer Service, Sales, and Production Planning. Such initiatives can ensure that the workforce is well-equipped to meet the evolving needs of various industries. For job seekers, understanding the demand for specific skills can guide them in prioritizing their skill development and improving their employability in competitive job markets.

Additionally, the distinct patterns of skill demand across industries can help job seekers target their efforts toward sectors where their skills are most valued. Focusing on high-demand skills such as Supply Chain or Teaching can provide job seekers with a competitive advantage, as these competencies are widely sought after in many sectors.

However, there are several limitations to this study. The analysis primarily focuses on the demand for skills without considering broader contextual factors, such as local or global economic conditions, which can also influence labor market trends. As Aloshyna and Kozenkov [26] pointed out, social, economic, and legal factors play a critical role in shaping labor market dynamics, and these factors were not explored in this research. Future studies could incorporate such variables to offer a more comprehensive understanding of the labor market.

Another limitation is that the study presents descriptive data without delving into the reasons behind the variations in skill demand. A deeper analysis, potentially using methods like K-Means clustering, could help uncover the underlying factors driving demand for specific skills, as seen in Miraftabzadeh et al. [25] research on energy systems. This type of analysis could reveal critical trends and causes behind shifts in skill requirements.

Furthermore, the study does not consider other important factors, such as job experience, location, or industry-specific nuances, which significantly influence hiring decisions. As highlighted by Kester et al. [30] and Fisher et al. [31], factors like geographic proximity and professional experience play a key role in recruitment, and understanding their impact would provide a more holistic view of labor market dynamics.

5. Conclusion

This study highlights the importance of understanding the skills required across various industries and the influence of factors such as location and experience level in shaping job opportunities. By applying the K-Means Clustering algorithm, the research provides a systematic approach to grouping jobs based on these critical factors, facilitating a more efficient and personalized job search process. The findings emphasize the high demand for skills such as Customer Service, Sales, and Production Planning, while also underscoring the importance of specialized skills like Medical Research in specific sectors.

The study offers valuable insights for both job seekers and policymakers. Job seekers can better tailor their career development and job search strategies by understanding which skills are most in demand across industries. Policymakers can utilize these insights to design targeted training and development programs that align with the current needs of the labor market, ensuring a well-equipped workforce.

However, the study is not without limitations. It primarily focuses on skill demand, without accounting for broader socio-economic factors or the underlying causes of skill demand shifts. Future research should explore these factors in greater depth, using advanced clustering techniques and broader datasets. Despite these limitations, this research provides a solid foundation for enhancing the job search experience and improving labor market efficiency.

6. Declarations

6.1. Author Contributions

Conceptualization: V.K.P., P.S.; Methodology: V.K.P., P.S.; Software: V.K.P.; Validation: P.S.; Formal Analysis: V.K.P.; Investigation: V.K.P.; Resources: P.S.; Data Curation: V.K.P.; Writing – Original Draft Preparation: V.K.P.; Writing – Review and Editing: P.S.; Visualization: V.K.P.; 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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