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Job Clustering Based on AI Adoption and Automation Risk Levels: An Analysis Using the K-Means Algorithm in the Technology and Entertainment Industries

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Abstract

This study explores job clustering based on AI adoption levels and automation risks in the technology and entertainment industries using the K-Means algorithm. By applying K-Means clustering, jobs were grouped into five clusters based on their AI adoption and susceptibility to automation. The analysis revealed that Cluster 1, with roles such as software engineers and data scientists, exhibited higher AI adoption and lower automation risks, making these positions more resilient to automation. In contrast, other clusters reflected varying degrees of AI integration and automation vulnerability, offering insights into workforce trends. Principal Component Analysis (PCA) and a heatmap of salary distributions further highlighted the economic implications of these clusters, with Cluster 3 representing the highest-paying roles. The findings suggest the importance of tailored upskilling and reskilling strategies to address the challenges of workforce displacement in AI-driven environments. This study provides actionable insights for workforce planning in industries facing rapid technological transformation.

Keywords: AI Adoption, Automation Risk, K-Means Clustering, Workforce Planning, Technology and Entertainment Industries

1. Introduction

The rapid development of AI technologies has driven a fundamental transformation in how workplaces operate, leading to significant implications for job automation and workforce resilience [1]. With advancements in machine learning and robotics, AI systems can replicate human cognitive functions, automating routine tasks and potentially displacing roles traditionally reliant on manual labor [2]. This automation trend poses clear risks, including job redundancy, socioeconomic disparities, and fragmented insights due to diverse methodological approaches in research [3]. Moreover, the integration of AI in the workplace necessitates finding a balance between leveraging technological efficiency and mitigating the potential negative impacts on employment. Understanding AI's dual role as a catalyst for productivity and a source of workforce disruption is essential, underscoring the need for robust policy frameworks and strategic workforce development initiatives [1].

Advancements in AI and automation significantly impact jobs in both the technology and entertainment industries. In the technology sector, AI adoption is transforming job roles by requiring advanced skill sets and continuous adaptation, as highlighted by research showing systematic skill transformations in response to automation. In the entertainment sector, AI fosters innovations in content creation, personalized user experiences, and immersive technologies, which simultaneously create new opportunities for roles while potentially displacing traditional creative tasks [4]. While AI enhances productivity and operational efficiency across these industries, it also necessitates strategic policy interventions to manage workforce displacement and ensure equitable transitions in employment paradigms [5]. This dual impact underscores the importance of adaptive strategies and ongoing research to balance technological benefits with job security and workforce resilience [5].

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A critical aspect of developing effective workforce strategies involves understanding the levels of AI adoption, which helps in systematically clustering jobs based on their vulnerability to automation risks [6]. By evaluating the extent of AI integration across industries, stakeholders can identify clusters of jobs that are highly susceptible to displacement, as well as those that may evolve with complementary technologies [6]. This analysis supports targeted upskilling and reskilling initiatives and the formulation of adaptive policy measures to address sector-specific challenges. Detailed insights into the rate and depth of AI adoption allow policymakers and industry leaders to anticipate shifts in workforce dynamics, enabling them to tailor interventions that mitigate adverse impacts while fostering innovative labor market solutions [6].

Mapping jobs based on AI adoption levels and automation risks requires a multidimensional evaluation of how AI technologies are integrated into workplaces and the susceptibility of various occupations to automation. Research shows that roles with repetitive or low-skilled tasks, such as assembly line work and data entry, are at higher risk of automation as AI adoption increases. Empirical studies also highlight the impact of AI on regional employment, contributing to job displacement, especially in areas where automation complements or replaces human tasks [7]. However, the diverse methodologies across studies have led to fragmented insights, complicating the development of unified mapping frameworks [3]. Therefore, a comprehensive approach should combine quantitative analyses of AI exposure levels with qualitative assessments of sector-specific risks to inform effective policy interventions and reskilling programs [8].

Understanding the varying characteristics of jobs in the technology and entertainment industries is crucial for effective workforce strategies. In the technology sector, jobs require advanced technical skills, and as AI adoption increases, there is a potential for skill gaps to widen [9], [10]. In contrast, the entertainment industry is driven by creativity, where routine tasks are less common, but technological adoption still impacts production and distribution processes. By mapping these differences, policymakers can better address sector-specific automation risks and opportunities, balancing technological proficiency in technology sectors with creative processes in entertainment [11]. Designing training strategies to meet the evolving needs of both sectors presents a challenge, requiring adaptive curricula that integrate upskilling and reskilling initiatives [12]. Customizing these strategies for each sector is essential to ensuring workforce resilience in the face of automation and fostering a sustainable transition into the future labor market [13], [14].

Analyzing job clustering based on AI adoption and automation risk levels requires applying quantitative cluster analysis techniques to classify occupations by their exposure to technological integration. [6] further explain that AI's multifaceted impact on job roles creates distinct clusters, with roles facing higher automation risk often needing different intervention strategies. Additionally, [15] highlights that variations in skill levels and job characteristics contribute to differing automation vulnerabilities, reinforcing the need to segment the labor market. This clustering approach provides a clearer understanding of sector-specific impacts and informs policy interventions and reskilling programs to address the evolving workforce's challenges.

The goal of this study is to employ the K-Means algorithm to extract latent patterns among job roles in the technology and entertainment industries. This unsupervised learning method is favored for its simplicity and efficiency in partitioning datasets into clusters based on feature similarity. By incorporating features such as AI adoption levels, automation risk scores, and job-related competencies, the algorithm discerns clusters representing varying job dynamics. This segmentation reveals differences between technology-driven roles and creative entertainment positions, identifying common transformation trends that inform tailored training programs and policy measures. Based on the cluster analysis, workforce planning recommendations should focus on tailored reskilling programs aligned with job group profiles. Sectors with high automation risks can benefit from identifying overlapping skill sets in alternative occupations [16]. Additionally, HR professionals should integrate AI-powered workforce analytics to forecast skill gaps and develop proactive upskilling initiatives [17], [18]. These strategies, combined with fostering cognitive flexibility, ensure an agile workforce that can navigate the evolving landscape of AI adoption and automation risks in technology and entertainment sectors.

The analysis of AI adoption and automation risks significantly impacts HR management and business strategy in the technology and entertainment industries by enabling more targeted talent management and strategic decision-making.

By clustering jobs based on these factors, HR professionals can identify specific skills gaps and tailor reskilling and upskilling programs to meet the workforce needs of the future. Additionally, business leaders can leverage these insights to optimize resource allocation and develop proactive strategies that balance technological integration with human capital development [19]. This data-driven approach not only helps identify emerging roles and operational trends within each industry but also promotes agile workforce planning and competitive differentiation. Ultimately, integrating cluster findings into HR and business frameworks enhances decision-making, ensuring effective talent management and robust strategic adaptability in rapidly evolving, AI-driven environments [19].

AI adoption is reshaping job structures by eliminating low-skilled, routine roles while driving the creation of new, high-skilled positions that require technical expertise and creative problem-solving [20]. The substitution effect, as discussed by Lin [21], highlights that jobs in sectors like manufacturing are more vulnerable to AI replacement, necessitating a shift toward hybrid roles combining human oversight with AI capabilities. These transformations can enhance productivity and restructure organizations, focusing more on analytical, strategic, and oversight functions [11]. To manage these changes, adaptive workforce planning and proactive upskilling and reskilling initiatives are essential to mitigate the social and economic impacts of AI-driven job displacement. Furthermore, tailored training policies, emphasizing continuous development of digital skills, are crucial for fostering sustainable job creation and aligning workforce competencies with sector-specific needs [22], [23].

2. Literature Review

K-means clustering is an unsupervised learning algorithm that partitions datasets into k clusters by minimizing within-cluster variances, with each data point assigned to the nearest centroid [24]. The algorithm's performance often hinges on determining an optimal number of clusters, typically achieved through the elbow method, which evaluates the relation between cluster variability and the within-cluster sum of squares to identify the optimal number of clusters [24]. Its theoretical appeal lies in its simplicity and computational efficiency, making it suitable for large-scale data processing [24]. Applications span multiple industries: in medicine, K-means has been applied to cluster phenotypic variations in scoliosis patients, revealing underlying biological heterogeneity Gardner et al. [25] in behavioral research, it groups service employee response profiles, revealing diverse attitudinal patterns Namin et al. [26] and in modern power systems, it optimizes the integration of renewable resources through the analysis of complex operational data. Additionally, maritime studies leverage K-means to determine representative operational profiles from AIS data, facilitating improved design efficiencies in shipbuilding [27].

Research shows that AI adoption substantially reshapes job types and task allocation, influencing the division of labor between humans and machines. Çolak [28] discusses how AI automates routine roles in the tourism industry, which shifts human involvement toward creative and customer-focused tasks. Concurrently, Ludec et al. [29] highlight that AI-driven automation results in complex labor redistribution, where human effort is reallocated to supervise and complement sophisticated AI systems rather than merely executing routine processes. In SMEs, Rawashdeh et al. [30] observed that automating accounting tasks prompts a redefinition of job roles, emphasizing the need for human judgment in strategic areas alongside enhanced efficiency. Furthermore, Yu et al. [31] provide a socio-technical perspective, examining how AI integration disrupts traditional job structures and necessitates new frameworks for contemporary labor divisions. Collectively, these studies underscore the transformative impact of AI adoption on employment configurations and task distributions across industries.

Advancements in AI have heightened automation risks in the technology and entertainment sectors by transforming jobs traditionally performed by humans. In technology, automated systems increasingly assume routine tasks such as coding, testing, and system maintenance intensifying concerns over job displacement and emphasizing the importance of retraining initiatives [32]. In parallel, the entertainment industry faces automation through generative AI applications that disrupt conventional content creation and curation processes, thereby shifting the balance of creative labor toward machine assistance [33]. These developments underscore the need for targeted policy measures that address both the rapid pace of technological change and the socio-economic implications for affected workers. Overall, the risk of automation in these sectors necessitates a comprehensive, industry-specific approach to workforce adaptation and sustainable employment practices [32], [33].

Previous research on job analysis and automation provides a multifaceted view of how advancements in artificial intelligence (AI) reshape work structures and labor market dynamics across various industries. A line of inquiry has focused on the impact of AI adoption on employee job satisfaction and task allocation. For example, Nguyen and Malik [34] examine how AI adoption influences job satisfaction, emphasizing that employees' perceptions significantly mediate the effects of automation on performance. Their study builds on earlier frameworks that underscored employee acceptance in the context of information technology systems, stressing the importance of job satisfaction as a retention mechanism in automated environments [34].

Complementing this perspective are econometric and general equilibrium analyses investigating sectoral reallocation as a consequence of automation. Hutschenreiter et al. [35] employ a general equilibrium model to demonstrate that automation induces a reduction in manufacturing employment, which may be counterbalanced by increased job creation in service sectors. This finding is significant as it highlights that, at an aggregate level, the shifting landscape of automation might not necessarily translate into a net loss of employment but rather into a reallocation of labor across sectors [35]. Similarly, Dauth et al. [36] explore the adjustment of labor markets to the proliferation of industrial robots, revealing that while productivity gains are evident, there are accompanying adverse impacts on wages and employment stability, underscoring the transformative pressures exerted by automation on job structures [36].

At a micro-level, research has delved into how AI adoption drives changes in job design and the division of tasks. Eftimov and Kitanovikj [37] provide insights into the antecedents of behavioral intentions toward utilizing AI for effective job (re)design. Their findings suggest that the expansion of AI in job crafting necessitates a strategic integration of regulatory and ethical considerations to safeguard employees' rights. Belloc et al. [38] contribute to the discourse by assessing the coevolution of job automation risk alongside workplace governance. Their study indicates a negative relationship between certain governance characteristics and the perceived risk of automation, advocating for stronger governance frameworks to mitigate the disruptive effects of automation [38].

Moreover, advanced analytical methods elucidate the complex interdependencies among job characteristics and automation risks. Lee et al. [39] use network analysis to map out how various occupational characteristics interrelate with susceptibility to automation. This approach illuminates the intricate network of factors that define job structures, providing a nuanced understanding that is critical for effective job analysis in an era of rapid technological change [39]. Complementing these findings, Sampson [40] focuses on professional services and introduces a framework that delineates the automation of tasks within complex jobs. Rather than a uniform displacement of entire roles, his research demonstrates that automation impacts discrete job tasks differently, prompting a paradigm shift toward task-level analysis within professional contexts [40].

In synthesis, the literature reviewed indicates that the implications of AI adoption on job analysis are not unidimensional but encompass both macroeconomic shifts and micro-level task reallocations. Studies by Nguyen and Malik [34], [35] and Dauth et al. [36] provide empirical evidence of macro-level labor market adjustments, while investigations by Eftimov and Kitanovikj [37], Lee et al. [39], and Sampson [40] elucidate the task-level and governance aspects of automation. This integrated perspective is crucial for designing policy interventions and management strategies aimed at mitigating the negative impacts of automation and fostering a balanced, future-oriented workforce.

3. Methodology

Figure 1 illustrates the steps involved in implementing the K-Means Clustering algorithm for data analysis.

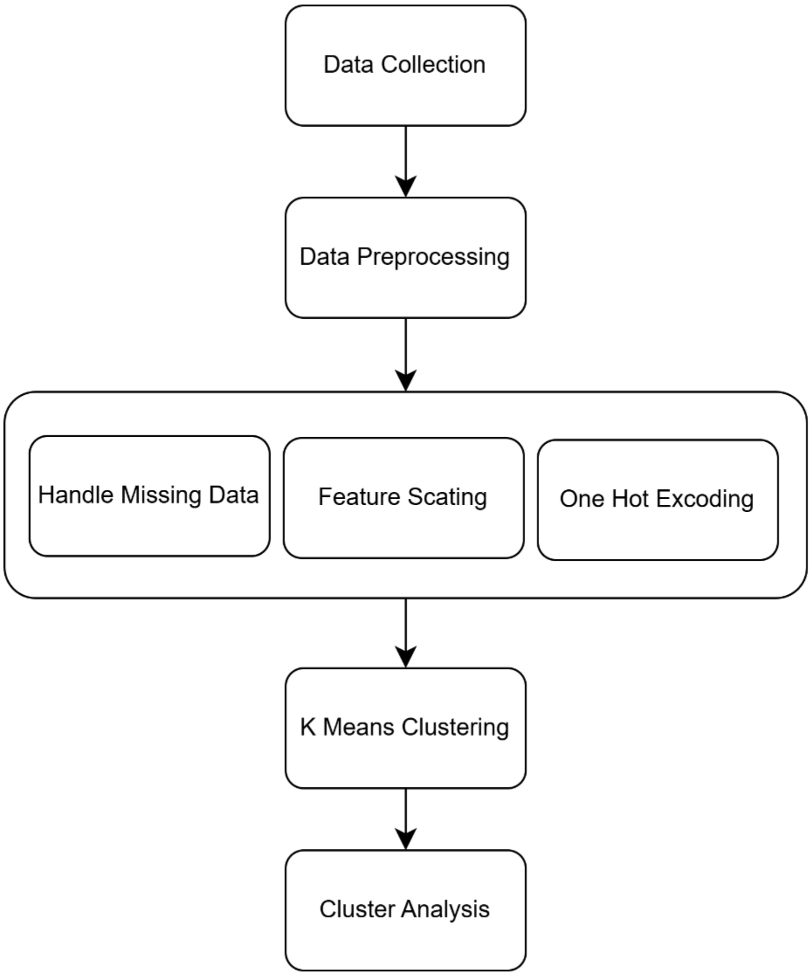

Figure 1. Research Methodology

3.1.Data Collection

Data collection was conducted through a combination of methods to ensure the completeness and accuracy of information related to AI adoption and automation risks in jobs. Surveys were used to collect quantitative data on the levels of AI adoption and automation risks across various job roles in the technology and entertainment industries, with respondents providing insights into how their jobs are impacted by AI and automation. In-depth interviews with industry experts and HR managers helped gain deeper contextual understanding of AI implementation in workplaces and its effects on automation risks in different job functions. Additionally, secondary data from industry reports, previous research articles, and relevant publications were utilized to provide a broader context on the long-term impacts of AI and automation on jobs in both sectors. This comprehensive data collection approach supported the application of K-Means clustering to identify patterns and relationships in job characteristics within these industries.

In this study, several variables were used to analyze job clustering based on AI adoption levels and automation risks. AI adoption levels measure the extent to which artificial intelligence has been integrated into job functions, categorizing jobs from low to high adoption based on the degree of AI technology utilization. Automation risks assess the potential for job replacement or significant alteration due to automation technologies, categorizing jobs into low, medium, or high-risk levels based on factors such as task repetitiveness and complexity. Additional relevant features include job functions, which refer to the specific tasks and responsibilities associated with the job, and industry, which helps differentiate between sectors like technology and entertainment, where the adoption of AI and automation may vary. Job size, which includes job complexity, required skills, and organizational size, and work environment, which evaluates the degree to which jobs are adaptable to automation, also play crucial roles in understanding how jobs are clustered. These variables collectively support the clustering analysis, providing a detailed understanding of how AI and automation influence job structures across industries.

3.2. Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset for clustering analysis. First, missing data is handled to ensure completeness and consistency. For numerical features, such as Salary_USD, missing values are imputed using the mean or median, ensuring that the data is not biased by extreme values. For categorical features, such as AI_Adoption_Level and Automation_Risk, missing values are either imputed with the most frequent category or excluded. This process ensures that all features are complete and usable for clustering without introducing bias.

Next, feature standardization is applied to numerical data to ensure that all features contribute equally during the clustering process. StandardScaler is used to scale the numerical values, transforming them to have a mean of 0 and a standard deviation of 1. This step is vital, as features with larger ranges could otherwise dominate the clustering algorithm. Additionally, categorical variables are transformed into a suitable format for K-Means clustering using One-Hot Encoding. This process creates binary vectors for each category, allowing the algorithm to process them effectively. These preprocessing steps ensure that the data is well-structured and ready for analysis, leading to more accurate and meaningful clustering results.

3.3. K Means Clustering

K-Means Clustering is a popular unsupervised machine learning algorithm used to group data points into clusters based on their similarities. In this analysis, K-Means was applied to group jobs based on AI adoption levels and automation risks. The process begins by initializing a predefined number of clusters (in this case, five clusters). Jobs are then assigned to the nearest cluster center based on their feature values, such as AI adoption and automation risk, using the Eulidean distance formula:

$$d(x, a) = \sqrt{\sum_{i=1}^{n} (x_i + c_i)^2} \tag{1}$$

x represents a data point, *c* represents the center of the cluster, and *n* is the number of features. The algorithm iterates by recalculating the mean (centroid) of the data points within each cluster and adjusting the cluster assignments. The centroid of each cluster is updated using:

$$\mathrm{C}_k = \frac{1}{N_k} \sum_{i \epsilon C_k} x_i \tag{2}$$

c_k represents the centroid of cluster *k*, N_k is the number of data points in cluster k_1, and C_k is the set of data points in cluster *k*. This process continues until convergence is achieved, meaning that the assignments of jobs to clusters no longer change, and the cluster centers stabilize.

To determine the optimal number of clusters, two methods were employed. The Elbow Method plots the Within Cluster Sum of Squares (WCSS) against different values of *k* (the number of clusters). WCSS is calculated using:

$$WCSS = \sum_{k=1}^{K} \sum_{i \epsilon C_k} d(x_i, c_i)^2 \tag{3}$$

K represents the total number of clusters, C_k is the data in cluster *k*, and $d\ (x_i,\ c_k)$ is the distance between data point x_1 and the centroid c_k . The optimal *k* is identified at the "elbow" point, where the rate of decrease in WCSS slows down, indicating that adding more clusters does not significantly improve the clustering. The second method, the Silhouette Score, evaluates how well-separated and compact the clusters are by measuring how similar each data point is to its own cluster compared to other clusters. The silhouette score is calculated using:

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$$s(i) = \frac{b(i) - a(i)}{max\ (a(i), b(i))} \tag{4}$$

$a(i)$ represents the average distance from point i to all other points in the same cluster, and $b(i)$ represents the minimum average distance from point iii to points in the nearest cluster. A score close to 1 indicates well-defined clusters. By using both methods, the most suitable number of clusters was determined, ensuring that the job groups accurately reflect the variations in AI adoption and automation risk. These steps help provide meaningful insights into how jobs are distributed across different levels of AI integration and automation risks.

3.4. Cluster Analysis

After applying K-Means Clustering, descriptive statistics were computed for each cluster to analyze their characteristics. For numerical features, the mean was calculated to represent the central tendency of each cluster, while for categorical features, the mode was used to identify the most common category within each cluster. To assess the quality of the clustering, the Silhouette Score was employed. This metric evaluates how well each data point fits within its assigned cluster compared to other clusters. A score close to 1 indicates well-separated clusters, confirming that the grouping is meaningful. Additionally, ANOVA tests were performed to statistically compare the differences between clusters. These tests help determine if the characteristics of the clusters are significantly different, offering insights into the distinct nature of each group.

For visualization, PCA was used to reduce the dimensionality of the data, transforming it into a 2D space for easier interpretation. PCA helps in understanding how the clusters are distributed across the features and reveals patterns that are not immediately obvious in high-dimensional data. Furthermore, Radar Charts were utilized to visually display the defining features of each cluster. These charts provide a clear and intuitive way to compare the characteristics of the clusters, showing how they differ in terms of AI adoption and automation risk. By combining statistical analysis and visual representation, this approach enables a comprehensive understanding of the cluster profiles, helping to interpret the underlying patterns in the data.

4. Results and Discussion

4.1. Cluster Analysis

The results of the K-Means clustering are presented in Figure 2, which illustrates the distribution of clusters in the dataset. The chart visualizes how the jobs are grouped across five clusters based on AI adoption levels and automation risks. Cluster 1 has the highest count of jobs, indicating that a significant portion of the workforce in the technology and entertainment industries falls into this category. Clusters 0, 2, 3, and 4 represent fewer jobs, each with distinct characteristics in terms of their AI adoption and automation risk profiles.

From this distribution, it becomes clear that Cluster 1 is the dominant group, suggesting that jobs in this cluster might have a higher degree of AI adoption and lower automation risk, making them more resistant to automation. Meanwhile, the other clusters represent varying degrees of AI integration and automation risks, providing insights into the diversity of job types in these industries.

These clusters will be further explored in subsequent sections to uncover the specific characteristics of the jobs in each group, including their reliance on AI technologies and the likelihood of being automated.

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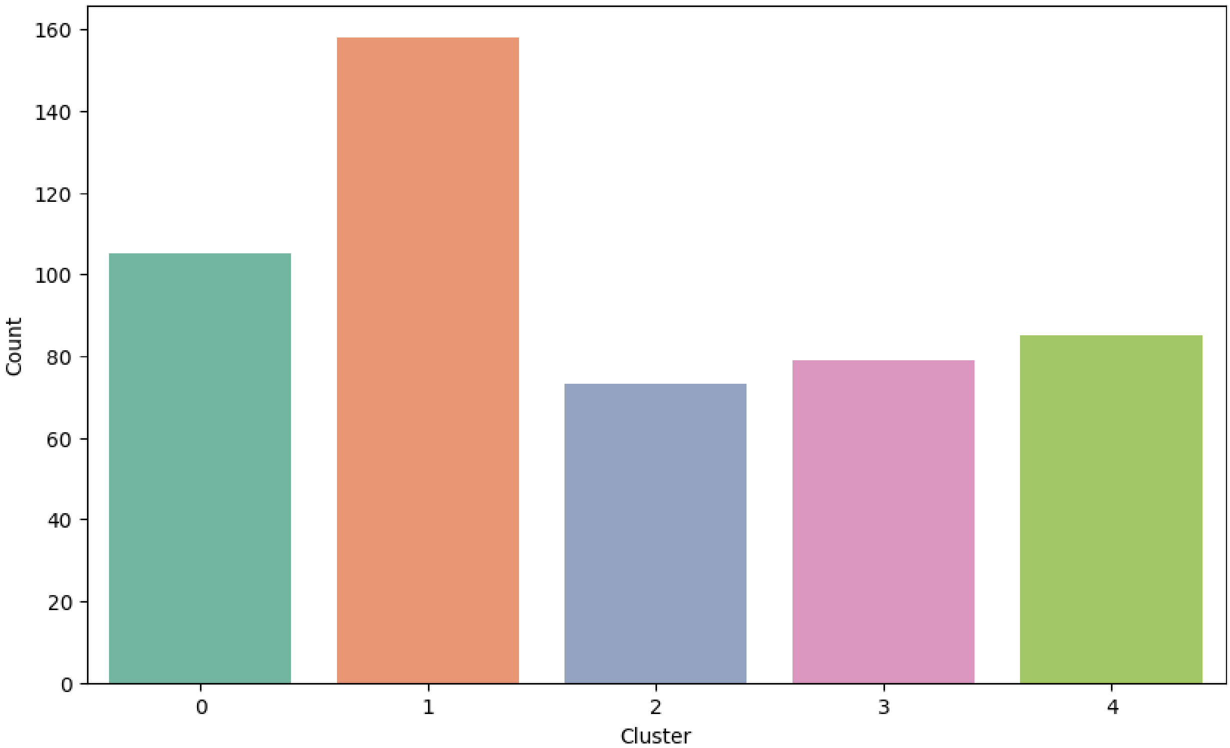

Figure 2. Distribution of Clusters

Figure 3 illustrates the cluster centers for each of the five clusters, providing a detailed comparison of various features that define each group of jobs. The figure highlights how different features, such as job titles, industries, AI adoption levels, and automation risks, contribute to the characteristics of each cluster. Each cluster is represented by a set of values for the features, with notable differences across clusters. For instance, Cluster 0 appears to have a higher concentration of jobs in Sales and Marketing roles, while Cluster 1 is strongly associated with Software Engineering and Data Scientist positions, reflecting higher AI adoption and lower automation risk. Additionally, the industry distribution in the clusters shows that Cluster 1 is predominantly from the Technology industry, while Cluster 3 includes jobs from industries like Entertainment and Retail, which may be more prone to automation. The figure provides a clear representation of how each cluster varies based on the job characteristics and is essential for understanding the segmentation of jobs based on AI adoption and automation risks.

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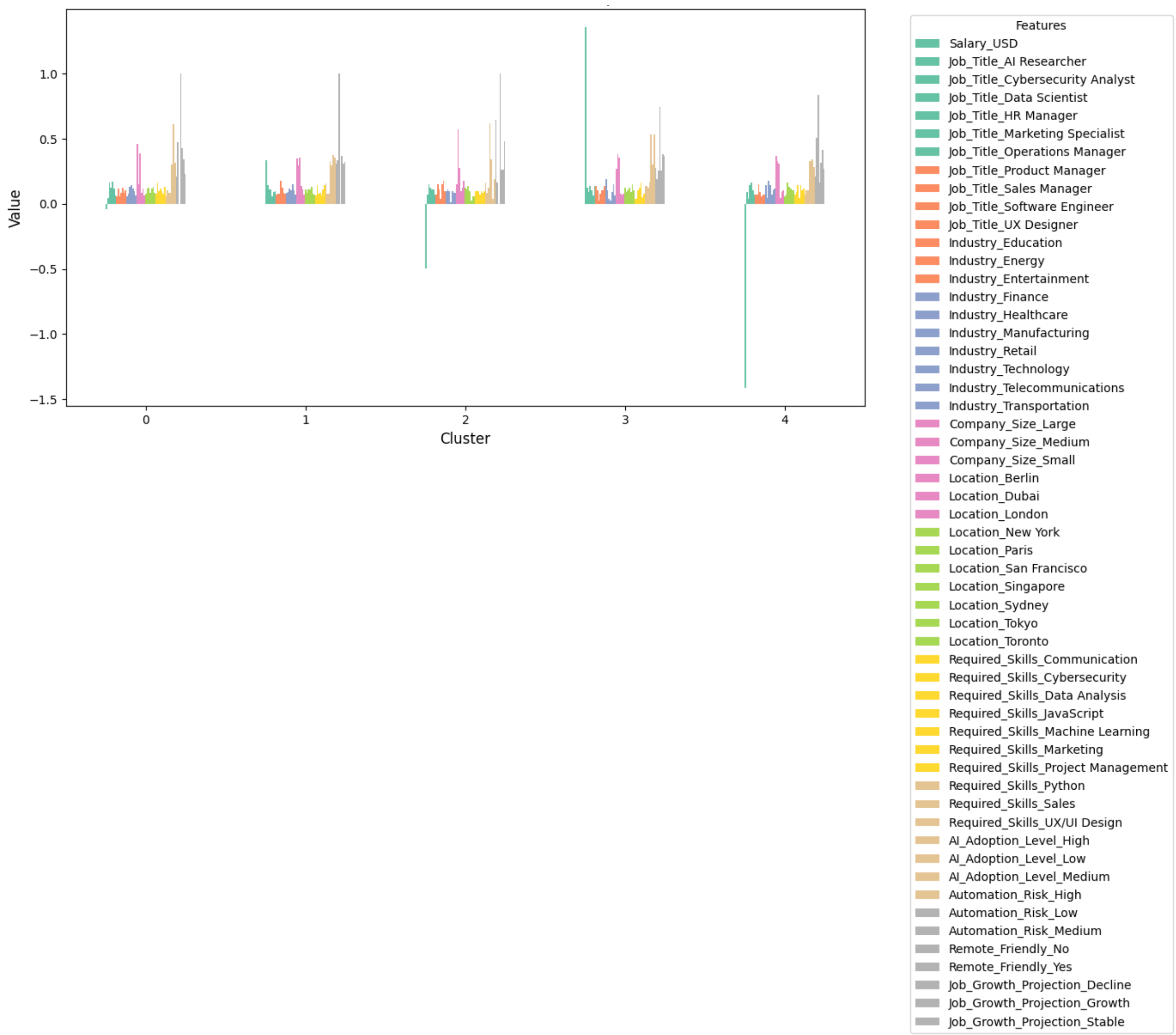

Figure 3. Cluster Center-Characteristic Comparison

Figure 4 provides a visual representation of the clustering results after applying PCA to the data. The plot displays the distribution of jobs across the first two principal components, PC1 and PC2, which are derived from the multidimensional feature space that includes AI adoption levels, automation risks, and other relevant features such as job titles, industries, and skills.

From the plot, we can observe that Cluster 1 (represented in orange) and Cluster 0 (green) are the most distinct and well-separated from the other clusters. This indicates that jobs in these clusters are characterized by significant differences in terms of AI adoption and automation risks. For instance, jobs in Cluster 1, which are typically associated with higher AI adoption and lower automation risk, are positioned towards the right of the plot, while Cluster 0, which might contain jobs with moderate to high automation risk and lower AI integration, appears on the left side. This suggests that Cluster 1 jobs are more resilient to automation and tend to be in areas that embrace advanced AI technologies, such as data science or software engineering roles.

Clusters 2, 3, and 4 (shown in different colors such as blue, pink, and light green) show overlapping distributions, indicating that these jobs might share similarities in terms of their AI adoption levels and exposure to automation risks. While the clusters are distinguishable, there is less clear separation compared to Clusters 0 and 1, which suggests that the jobs within these clusters may have more varied characteristics, with mixed levels of automation risk and AI integration.

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The PCA visualization in Figure 4 serves as a powerful tool for confirming the findings from the K-Means clustering analysis. It provides a clearer understanding of how the jobs are grouped based on their AI adoption and automation risks, as well as the relationships between these two variables. This visual representation supports the hypothesis that jobs in different clusters are affected in distinct ways by the ongoing transformations driven by AI and automation technologies.

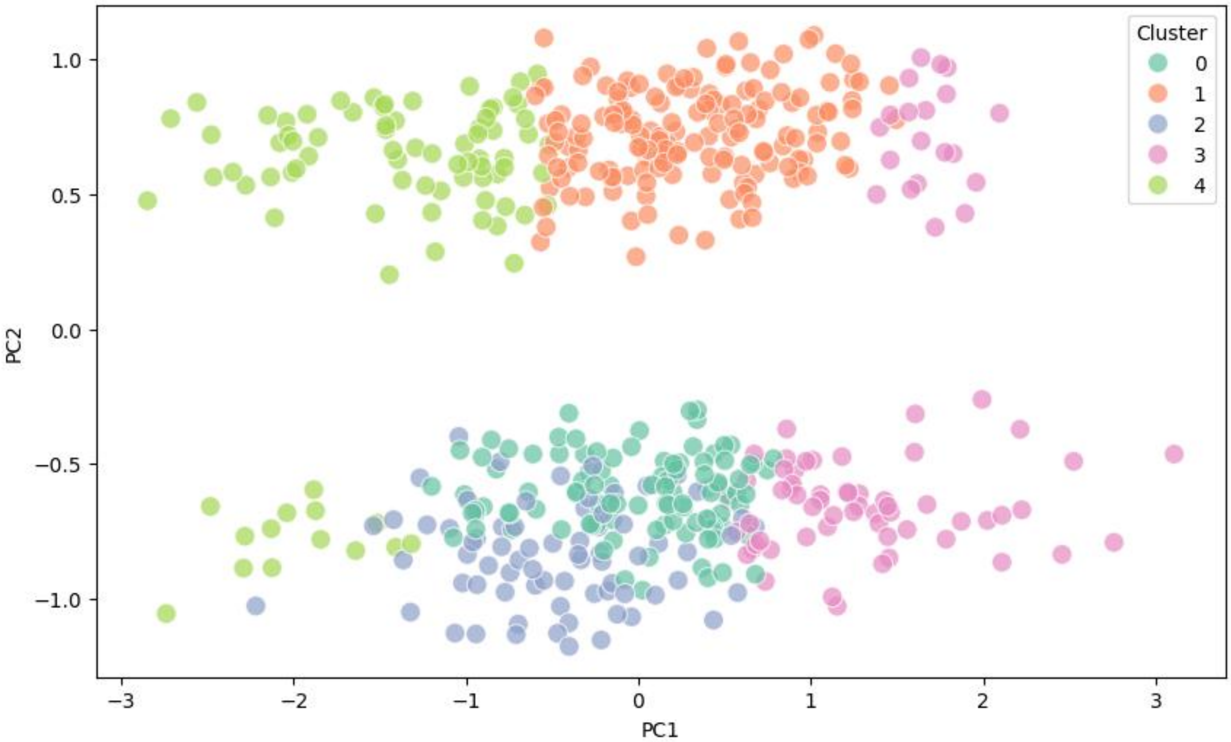

Figure 4. PCA of Cluster

Figure 5 presents a heatmap illustrating the average salary (in USD) for each of the five clusters. The color intensity indicates the relative value of Salary_USD in each cluster, with a gradient from blue (lower salaries) to red (higher salaries). From the heatmap, we can observe that Cluster 3 has the highest average salary at 118,988.04 USD, suggesting that jobs in this cluster tend to be associated with higher-paying positions. In contrast, Cluster 2 has the lowest average salary at 81,113.88 USD, indicating that jobs in this cluster are generally lower-paying. Clusters 0, 1, and 4 show moderate salary values, with Cluster 1 having an average of 98,126.09 USD and Cluster 4 at 62,244.53 USD.

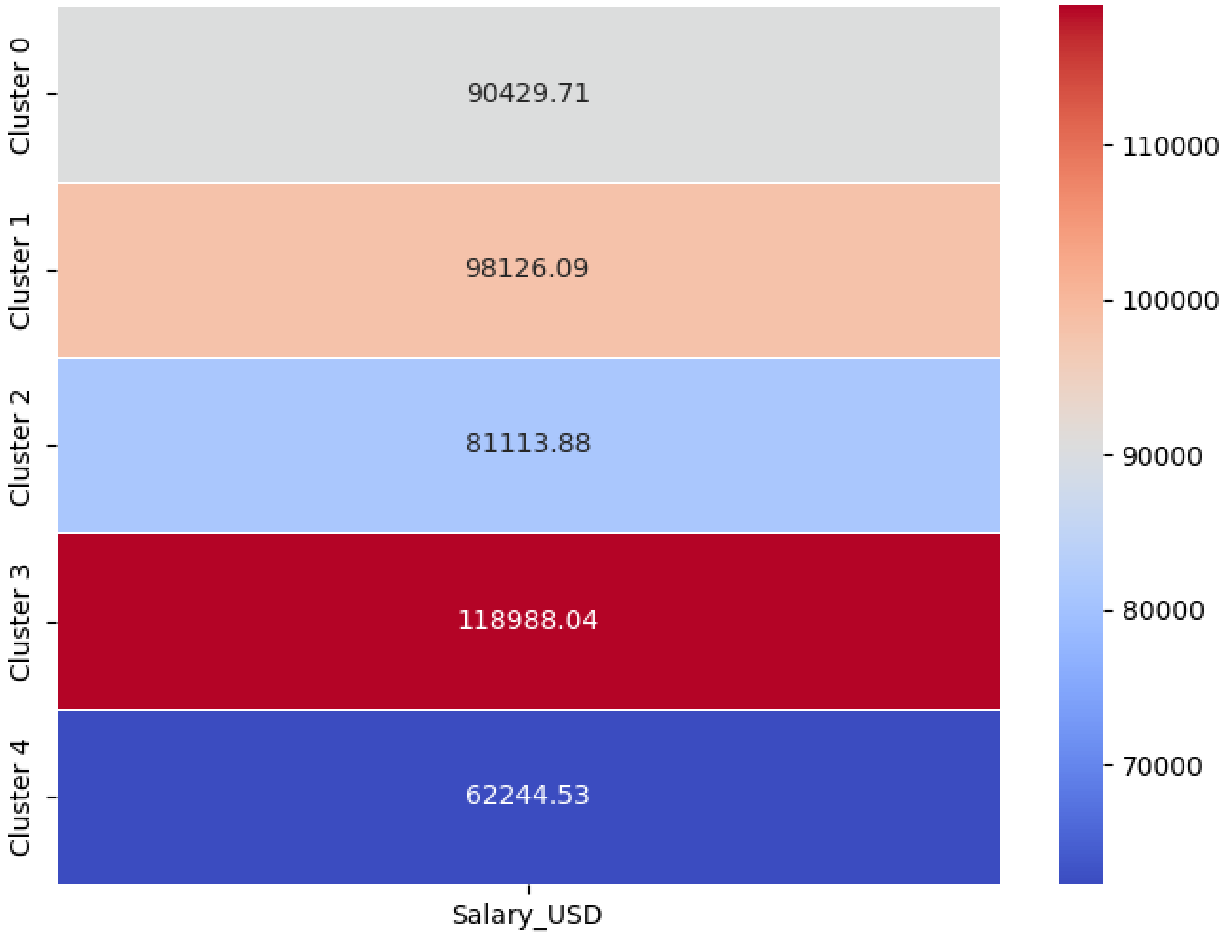

Figure 5. Heatmap of Numerical Features per Cluster

This heatmap is a valuable tool for understanding the financial characteristics of the jobs within each cluster, providing insights into how AI adoption and automation risks correlate with salary levels across different job types in the technology and entertainment industries. These findings will be further discussed in the next sections to explore the relationship between salary and other features such as AI adoption and automation risk.

As shown in Table 1, the mode (most frequent value) of categorical features for each cluster provides an insightful summary of the characteristics of jobs grouped by AI adoption and automation risks. For Cluster 0, the most common job title is HR Manager, predominantly in the Retail industry, with large companies located in Tokyo. This cluster requires Cybersecurity skills and has medium AI adoption and medium automation risk, with most jobs being remote-friendly and a decline in job growth projection. Cluster 1, on the other hand, features UX Designers in the Technology industry, with small companies in Berlin. These jobs demand Python skills, have medium AI adoption, and are at a high risk of automation. Jobs in Cluster 1 are not remote-friendly and show a decline in job growth. Cluster 2 represents jobs like Cybersecurity Analysts in the Energy sector, with medium-sized companies located in London. This cluster has high AI adoption, low automation risk, and jobs that are remote-friendly with a stable job growth projection. In contrast, Cluster 3, which includes Data Scientists in the Finance industry, shows low AI adoption and high automation risk, and jobs are located in Tokyo. These jobs are remote-friendly and expected to grow. Lastly, Cluster 4 has jobs like HR Managers in the Manufacturing industry, with large companies in San Francisco. This cluster exhibits medium AI adoption, medium automation risk, and a growth in job opportunities, but with positions that are not remote-friendly.

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Table 1. Mode of Categorical Features for Each Cluster Based on AI Adoption and Automation Risks

Feature	Mode				
	Cluster 0	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Job Title	HR Manager	UX Designer	Cybersecurity Analyst	Data Scientist	HR Manager
Industry	Retail	Technology	Energy	Finance	Manufacturing
Company Size	Large	Small	Medium	Medium	Large
Location	Tokyo	Berlin	London	Tokyo	San Francisco
Required Skills	Cybersecurity	Phyton	Phyton	Machine Learning	Data Analysis
AI Adoption Level	Medium	Medium	High	Low	Medium
Automation Risk	Medium	High	Low	High	Medium
Remote Friendly	Yes	No	Yes	Yes	No
Job Growth Projection	Decline	Decline	Stable	Growth	Growth

Table 1 provides a comprehensive overview of the most common job characteristics for each cluster, highlighting key differences in job titles, industries, AI adoption, and automation risks. This detailed analysis helps in understanding how various factors influence job clustering, especially in terms of technological advancement and the potential for automation. By examining these characteristics, we gain valuable insights into workforce trends and can better anticipate the future needs of the job market in the technology and entertainment industries.

4.2. Discussion

The results presented in Figure 2 through Figure 5 offer a comprehensive view of how jobs in the technology and entertainment industries are clustered based on AI adoption levels and automation risks. As seen in Figure 2, the distribution of jobs across five clusters reveals that Cluster 1 has the highest count of jobs, suggesting that a large portion of the workforce in these industries falls into this category. This cluster is likely composed of jobs that exhibit a higher degree of AI adoption and lower automation risk, making them more resistant to automation, which aligns with previous research Çolak [28] on the role of AI in reshaping job structures.

Cluster 1, being the dominant group, likely represents positions that rely heavily on AI technologies, such as roles in software engineering and data science, where the adoption of AI has enhanced productivity while reducing the likelihood of automation. Figure 3 highlights how different job titles, industries, and skills contribute to the cluster characteristics. Jobs in Cluster 1 predominantly belong to the Technology industry and require skills like Python. In contrast, Cluster 0 contains jobs in Retail, such as HR Managers, that rely on Cybersecurity skills, but with a medium level of AI adoption and automation risk, which may not be as highly automated as those in technology sectors.

Moreover, Figure 4, which applies PCA, visually confirms the separation between Cluster 1 (orange) and Cluster 0 (green). The clear distinction between these two clusters, especially along PC1 and PC2, suggests that Cluster 1 represents jobs with advanced AI integration and lower automation risks, while Cluster 0 indicates positions with a mix of moderate AI adoption and higher susceptibility to automation. These findings align with earlier studies indicating that AI adoption and automation risk are key factors that influence job characteristics [29], [28].

The heatmap in Figure 5 further enhances our understanding by showing the average salary across the clusters. The highest average salary is observed in Cluster 3, which likely includes jobs such as data scientists and other high-demand tech roles that command higher wages. In contrast, Cluster 2, which includes jobs with lower AI adoption and automation risk, has the lowest average salary. This provides insight into how AI adoption and automation risks may not only affect job roles but also have an economic impact on the salaries within each cluster.

Table 1 offers a detailed overview of the mode of categorical features for each cluster, reinforcing the findings from the previous figures. For example, Cluster 0 includes jobs in the Retail industry with a focus on Cybersecurity, while Cluster 1 is predominantly in the Technology industry and includes roles requiring Python skills. The AI adoption level for Cluster 1 is higher, while Cluster 3, which contains Data Scientists in Finance, is characterized by low AI adoption and high automation risk. This table succinctly captures the essential characteristics of each cluster, providing a clear framework for understanding how AI adoption and automation risks affect job functions and industries.

In conclusion, the clustering analysis, supported by PCA visualization and heatmap analysis, provides valuable insights into how AI adoption and automation risks shape job characteristics across different sectors. These findings suggest that while AI adoption increases in certain industries, automation risk continues to be a significant concern, particularly for roles in industries like Retail and Finance. The need for tailored workforce adaptation strategies and policies to mitigate automation risks is evident, with a focus on upskilling and reskilling initiatives that can enhance the employability of workers in AI-driven environments. These conclusions align with previous research that emphasizes the role of AI adoption in reshaping labor markets and the importance of addressing automation risks to ensure a balanced workforce in the future [32], [33].

5. Conclusion

This study employed the K-Means clustering algorithm to group jobs in the technology and entertainment industries based on AI adoption levels and automation risks. The clustering analysis revealed distinct groupings of jobs, with Cluster 1 showing the highest count of jobs, indicating a dominant segment characterized by higher AI adoption and lower automation risk. This cluster mainly includes roles like software engineers and data scientists, jobs which are less susceptible to automation due to their reliance on advanced AI technologies. In contrast, other clusters exhibited varying levels of AI integration and automation risks, providing insights into the diverse job functions across sectors.

The PCA visualization confirmed the clear separation between Cluster 1 and Cluster 0, highlighting jobs that embrace AI technologies and those with moderate AI adoption but higher automation risk. The heatmap analysis showed that jobs in Cluster 3 had the highest average salary, reflecting the higher-paying roles in sectors with advanced technological integration. These findings underscore the importance of understanding the evolving landscape of AI adoption and automation risks, which significantly influence job characteristics, including salary and skill requirements.

The results emphasize the need for tailored strategies to address automation risks and AI adoption across sectors. Workforce adaptation strategies, such as upskilling and reskilling initiatives, are crucial for enhancing the employability of workers in the face of automation. Furthermore, the findings align with existing literature on the transformative effects of AI on job structures and labor market dynamics, underscoring the importance of strategic workforce planning and policy interventions.

6. Declarations

6.1. Author Contributions

Conceptualization, M.S.H. and R.R.N.F.; Methodology, R.R.N.F.; Software, M.S.H. and D.A.D.; Validation, M.S.H. and R.R.N.F.; Formal Analysis, M.S.H. and R.R.N.F.; Investigation, M.S.H.; Resources, R.R.N.F. and D.A.D.; Data Curation, R.R.N.F.; Writing—Original Draft Preparation, M.S.H. and R.R.N.F.; Writing—Review and Editing, R.R.N.F. and M.S.H.; Visualization, M.S.H. 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.

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Not applicable.

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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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