iJournals: International Journal of Software & Hardware Research in Engineering
ISSN:2347-4890, ijournals.in/ijshre
Volume 13 Issue 10, October 2025

Exploring Special Needs Employee with Disabilities Analysis & its Impact on Indian Employment

Arick Agarwal

American International school Chennai, India

Email: arickagarwal@gmail.com

Vinay Vishwakarma

Mentor, On My Own Technology Pvt. Ltd. India

Email: vinay.vishwakarma@omotec.in

DOI: 10.26821/IJSHRE.13.10.2025.131012

ABSTRACT

People with disabilities constitute approximately 2-21% of the population in India, they still find it difficult to find a job despite the implementation of government programs for inclusive growth. Systemic barriers continue to restrict the participation of people with disabilities in the workforce even with progressive legislation and government initiatives making an effort toward inclusive employment. The factors that have left the employment level at a low ratio of 34% even within this group are limited access to education and workplace inaccessibility, and stigma in the society. Wage differentials further widen the gulf of economic inequality; whereby disabled workers usually earn much lower wages than their non-disabled counterparts. This study aims to evaluate trends regarding employment of people with disabilities along with identifying the significant factors that determine accessibility to jobs, wage differentials, and retention rates. Further, it intends to place policy recommendations based on data for improving inclusive employment in India.

This research used Exploratory Data Analysis (EDA) techniques for investigating employment, representation in industries, wage gaps, and assistive technology. Through univariate, bivariate, and multivariate analysis, trends emerged across disability types, educational qualifications, and workplace inclusivity. Predictive modeling techniques were used to determine how assistive technology and work-place policies impact the employment outcome. Geospatial and demographic analysis was included to showcase disparities in employment opportunities by region. The research findings show that higher education levels contribute substantially to employability, especially in knowledge intensive industries such as IT, healthcare, and finance. On the other hand, opportunities for employment of the disabled in the sectors of production and construction are disproportionately low. Access to assistive technologies was said to have improved job retention for 40% of respondents; however, persons with mental health issues experienced prolonged gaps in employment that would benefit from tailored workplace interventions.

Finally, this study offers 15 policy recommendations addressing more possible inclusive labor markets and recommends strengthening mental health support networks, encouraging inclusive hiring practices, making the integration of assistive tools mandatory, extending vocational training opportunities, and closing the digital divide. Data-driven policies are essential to assure equal employment opportunities and to close the socioeconomic gap between people with disabilities.

KEYWORDS

Disability Employment Inclusion, Employment Disparities in India, Predictive Analysis in Disability Employment, Workplace Accessibility Policies, Special Needs-Based Employment Barriers.

I INTRODUCTION

The employment scenario for persons with disabilities in India is a mixed bag of challenges and emerging opportunities. Although there is progressive legislation and increased awareness, employment is still at unwanted low levels, as only 34% of people with disabilities have jobs compared to the general workforce participation rate. Despite the government's policy and efforts towards inclusion by different organizations, the employment ratio of the disabled is still very low compared to their non-disabled peers [1]. In the past few years, the seriousness of both the government and corporate bodies has intensified in an effort to enhance this through different policies, skill development as well as workplace inclusive program initiatives and activities. This effort is directed towards overcoming the barriers-in triple features, which are physical accessibility, attitudinal barrier and skill gap, that persons with disabilities face regarding their lawful access to employment. To really get into the inclusive employment space, what would be most required for India is the sustained, innovative and cooperative action from both public and private sectors. The employment situation for persons with disabilities in India remains challenging despite constitutional provisions and legislative frameworks that back them in entering the employment market. As per the latest statistics, only about 34% of persons with disabilities in India are employed, revealing a wide gap in that when compared with the general population[2].

This becomes more disturbing when you realize that they form only a part of the 2.21% of India's total population as per the 2011 Census, representing over 26.8 million individuals, who are facing serious barriers toward economic participation[3]. Employment is further complicated with a clear urban-rural rural divide among these people as formal employment in most cases becomes even tighter within rural spaces because of the limited opportunities available as well as the lack of adequate infrastructure.

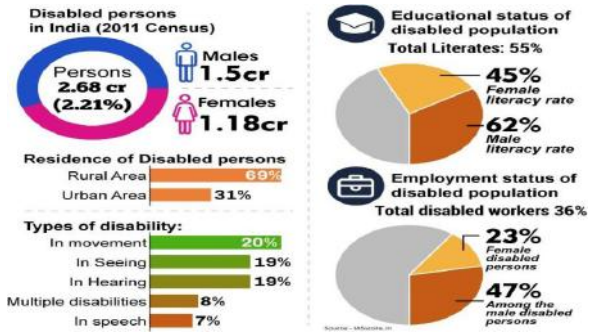


Fig. 1: Persons with Disabilities

Another important aspect is the study's focus on financial equity and income distribution. Even if they are equally qualified in their training and experience, the notion is that persons with disabilities tend to have less earning power compared to their able bodied counterparts. Financial outcomes are affected significantly by digital accessibility, employer policies, and types of industry. This study employs regression analysis and box plots to find the factors responsible for wage gaps and salary discrepancies. It also looks at how employer financial assistance and government schemes influence the economic viability of workers with disabilities. Educating the employability of persons with disabilities becomes necessary. The presence of variables on educational attainment and employment status in the dataset allows a thorough examination of the impact of higher education on job accessibility. Structured learning can get some people employed, but many need specific training and skill-building initiatives. This research evaluates how well the existing educational policies and vocational training have been serving to close the employment gap for the disabled. It will also look for industry preferences and employment trends particular to a sector to determine those sectors that might have increased inclusion rates. Employers have been keener on hiring people with brains, particularly in the information technology (IT), healthcare, and education sectors.

Digitization is the process of swiftly moving from manual labor to the digitized way of issuing instructions. Digital accessibility becomes integral in availing job openings. This study aims to examine the relationship between employment status and digital engagement, specifically focusing on digital literacy, personal computer usage, and internet accessibility. Digital accessibility significantly correlates with participation in an active workforce. This factor demonstrates the urgency of a digital inclusion policy aimed at closing

the technological gap for the disabled [4]. Another significant issue for discussion in this study is the relationship between job security and mental health. For persons who suffer from stress, depression, or other mental health conditions, moving forward in their careers or retaining a job often becomes difficult. It looks at how corporate policies around mental health can create that enabling environment and how valuable they may be in analyzing employment trends against cases of mental health conditions through case studies, time-series studies, and histograms. Building upon this, predictive modeling techniques will create more elaborate forecasts of employment outcomes based on digital access, type of industry, education, and type of disability. Feature importance analysis will pinpoint the critical factors influencing employment, enabling data-driven insights for employers, policymakers, and civil organizations to enhance workforce inclusion and decision-making.

The effect of modifications to corporate mental health policy on workplace inclusiveness will be investigated by examining the effects of mental health conditions on employment trends from case histories and histograms. Employment outcome predictions for further analysis were built using predictive modelling techniques on digital access, industry type, education, and disability type. An analysis of feature importance will help give data-driven recommendations to employers, lawmakers, and social organizations on the most important employment determinants. Finally, the study across several Indian states reveals the evolution of employment and urban-rural disparity across states concerning employment-related statistics[5]. Geospatial analysis would assist in pinpointing specific areas, namely those with low employment rates, that require immediate policy intervention. The influence of public policy and employer-led diversity initiatives on employment indicators at the sub-state level is studied in tandem so that relative employment disparity mitigation effectiveness can be gauged.

II LITERATURE REVIEW

The study by **Bachmann, Nadine, et.al. [6]** critically explores data-driven technologies and their contributions towards the UN Sustainable Development Goals (SDGs). This research consolidates heterogeneous prophecies of data analytics to show the power of data-driven decision making, predictive modelling, and resource optimization in making improvement toward economic, social, and environmental sustainability. This conceptual framework helps to understand the manner in which different data-driven means monitoring, forecasting, and risk assessment justify evidence-based policymaking. Moreover, by this, it shows how the real-time availability of data and AI-mediated insights find a productive connection between policy making and implementation for better governance and resource allocation in terms of sustainable development. However, it has several limitations that need attention regarding the use of data driven technologies towards SDGs. Data availability and inconsistent quality is a persistent challenge in developing regions with limited infrastructure and digital literacy. The study also mentions the ethical and security issues involved in data privacy, ownership of data and algorithmic bias that could skew decision-making processes. High energy consumption in computation raises the question of the environmental sustainability of this pursuit a contradiction in itself in pursuing SDGs. Scalable solutions to these problems do not adequately feature in this study, nor does it provide any elements of quantitative impact assessment of data-driven practices across SDG targets.

The study by **Nilika Mehrotra, et.al. [7]** offers an intersectional critique of the issues of disability, gender, and caste and how these marginal variables condition access and social experiences in India, with an economic shift as the context. The ethnographically informed empirical research then gives us to make a more nuanced claim about the systemic exclusions faced by Dalits with disabilities (in particular, women), in both work and social life. A consideration of state and NGO interventions further provides a critical reading regarding policy implications, with recourse to discussions on inclusive economic policies and accessibility. Thus, by exposing the layered complexity of marginalization, the study becomes a trigger for further research into the areas of social justice and equitable development. The study, however, while greatly encompassing, still lacks quantitative data for stronger empirical validation of its findings. While these last-mentioned studies follow an intersectional line of enquiry, there is also the need for further studies focusing on regional disparity in the access to resources. The study is mainly concerned with state NGOS

interventions but does not study the role of private sector initiatives in enhancing employment opportunities for Dalits with disabilities. Additionally, it makes no mention of the long-term consequences of globalization for economic accessibility of ostracized groups. Addressing these gaps could further enhance policy recommendations in inclusive economic development.

The study by **Gagan Chhabra, et.al. [8]** investigates systemic attitudinal and access barriers that young adults with visual impairments (YAVI) face in getting employment, which stresses the ubiquity of discrimination on the part of the employer globally. Through a comparative lens between Oslo and Delhi, the research adds novel insights into discrimination as an experience in contrasting socio-economic and policy landscapes. It is significant since the social model of disability and the concept of disablism have been used to frame the employer's biases, thereby bridging the understanding gulf concerning employment barriers across cultures. Furthermore, by incorporating qualitative narratives, the research uplifts the voices of marginalized people and presents stakeholders with evidence-based recommendations for increasing employment inclusivity. While the study offers valuable insights through comparison, it lacks an in-depth examination of policy interventions that could lessen employer discrimination. Since the research confines itself to Oslo and Delhi, its findings have limited transferability to other developed and developing nations. The sample size of 29 participants may not adequately represent the diversity in the employment experience of YAVI individuals. Additionally, the study comprehensively investigates employer discrimination in relation to recruitment without looking into barriers to retention, career advancement, or provision of accommodations. Longitudinal studies focusing on employment outcomes and quantitative approaches are recommended to further strengthen findings and enhance their application across different sectors.

The study by **Ladumai Maikho Apollo Pou, et.al. [9]** offers pivotal information regarding prevalence and determinants of multiple disabilities in India among the elderly population. The application of data from the India Human Development Survey (IHDS) allows for an extensive statistical examination of the socio-economic determinants of disability prevalence. The investigation finds economic vulnerability as the foremost predictor, stressing the urgent requirement for focused policy interventions. Next, it sheds light on the dearth of financial and social support for disabled older adults, and the significance of family structure in providing care. This study, thus, serves as a key information resource for social protection, geriatric health care policy, and disability inclusion in developing countries. Some limitations nonetheless exist statistically, and more studies may be indicated. While relying on IHDS data, extensive as it is, may overlook the extent of regional disabilities in some settings, particularly in rural and tribal pockets. A more thorough investigation of economic factors is warranted,

in addition to working on the psychological and mental health fronts. The study should also take gender-specific differences and their role in the progression of disability into account. In the future, longitudinal and qualitative approaches will be necessary to illustrate lived experiences, access to health care, and the effectiveness of government interventions in addressing the complications of elderly disability.

The study by **Ipsita Rakshit, et.al. [10]** highlights a critical intersection between disability, education, and child labor, and they look at how the disabled children in Tamil Nadu face these socioeconomic barriers. The impact-aspects of intervention through policies have been evaluated in quantitative terms by the study through the use of multinomial logit models and difference-indifference frameworks-the Tamil Nadu Disabled Persons Act, for instance. Also, the results would illustrate, firstly, how urban-rural divide in the accessibility of education and how type of disability varies from attendance in school to engaging in child labor among children. Thus, such facts could become quite useful for policymakers, educationists, or social welfare organizations working for inclusive educational policies and targeted interventions for disabled children. However, it has a qualitative void because it would have added dimensions of social stigmas, family contexts, or systemic barriers around disabled children, which are not taken into consideration. The entire study is also based on Tamil Nadu, hence restricting its

generalization for other states with varying socio-economic context. The study does not include any longitudinal impacts that educational policies may have had on the population beyond the Census of 2001-2011. This research thus does not find out any trend post higher education or vocational training. It identifies disparities but does not add any specific interventions or improvements to the policy, which would otherwise address these gaps. Future research should consider qualitative interviews, more extensive datasets, and assessments of policy impact.

The study by **Ramya Naraharisetti, et.al. [11]** explores employment discrimination faced by PWDs in a spatially analytical context in India, identifying specific employment demarcators for rural and urban vicinities. The study establishes a sounder database for policymakers in pursuing targeted and effective poverty alleviation programs by way of employing 2001 Census data, linear regression, and spatial autoregressive models. The analysis would show that disability type, gender, and literacy are important determinants of employment and highlight the pressing necessity for location-specific policy interventions addressing rural and urban barriers to employment. Furthermore, it underlines the need for inclusive workforce policies that confer access and economic opportunities on persons with disabilities. The research does have its shortcomings; the data used on the 2001 Census is certainly of great value but might not speak to changes that have occurred over the years in terms of socio-economical contexts and technological advancements affecting employment opportunities for persons with disabilities. The study has also not accounted for the emergence of new employment sectors like work-from-home and the digital workforce in terms of new pathways toward inclusion. The research has maintained a strong focus on spatial correlations, overlooking some qualitative characteristics associated with employment challenges such as workplace discrimination, adoption of assistive technologies, and gaps in policy implementation. Future inquiries would definitely benefit from carrying out a longitudinal data collection scheme that takes in qualitative aspects so that a more wholesome understanding of the dynamics of disability employment in India can be built up.

The study by **Vanmala Hiranandani, et.al. [12]** emphasizes, provides valuable insight into some of the socio-economic challenges that people with disabilities face in India. This study reviews the above topics through the prism of neo-liberal economic policies and emphasizes how such policies deny equitable share of economic growth to the disabled populations in employment, accessibility, education, and healthcare. That is why this assessment becomes important; it draws attention to the systemic marginalization of people with disabilities, especially in low-income strata, that demands an inclusive policy response. It would aid in developing a basis for policymakers and advocates who are working toward a redefinition of disability rights in India's dynamic economic context. The authors explore the general economic drivers behind disability inclusion but fail to provide any specific quantitative data with which to measure discrepancies in employment and accessibility. The study predominantly captures macroeconomic trends with scant appreciation for regional variations in rural contexts concerning disability rights. It also fails to capture the long-term ramifications of privatization on health and education for the disabled. It deserves to be weighed against other developing economies that are going through basically similar economic transitions. If these gaps were to be filled with empirical data and case studies, they would further give credence to the study and improve its policy recommendations.

The study by **Aasha Kapur Mehta, et.al. [13]** comprehensively sets out the framework for diagnosing chronic poverty in India through the extended duration of poverty, severity of poverty, and multidimensional deprivation. It emphasizes the geography and socioeconomics of poverty, generating valuable insights into the most vulnerable regions and communities. The area-based approach identifies dryland and forest-dependent

regions among those facing persistent economic deprivation and ecological stress. In contrast, the historic marginalization approach explains the continued systematic exclusion of scheduled castes, scheduled tribes, and agricultural laborers. This study marks a significant contribution to the policy discourse by evaluating the effectiveness of the current policies and creating an evidence-based argument toward poverty alleviation. Although the analysis of chronic poverty is quite well done, it does not investigate deeply the current economic transition, such as urban

migration, digital inclusion, and rural employment diversification. The bulk of the work is done within the historical data ambience; however, the study lacks to sufficiently track contemporary welfare programs impacted on marginalized communities. The intersectionalities of gender, disability, and poverty are not well talked about, which would limit applicability to other vulnerable populations. Moreover, the paper is limited in its theoretical engagement with bottom-up interventions or community adaptations that are crucial in strengthening the understanding of localized resilience building strategies against chronic poverty.

The study by **Ramachandra, Srikrishna S., et.al. [14]** provides relevant evidence about the restrictions imposed on persons with disabilities (KwD) in their pursuits of employment opportunities in the Indian IT and IT-enabled sectors. The findings underscore limitations due to physical access, workplace discrimination, and attitudinal biases toward PwDs, thus laying down empirically relevant evidence for inclusive employment policies. The study revealed that only 3.8% of employers had proper policies in place for hiring PwDs, hence showing an impending need for corporate inclusivity initiatives. The research has also highlighted how to use employer perceptions of 'seriousness' and 'commitment' of PwDs for a more equitable workforce. Nonetheless, the study has limitations that should lead to further investigations. First, it used a highly limited focus on the IT and IT supported sectors in Hyderabad, and thus it has little applicability in other industries and regions. Secondly, the study relied predominantly on self-reported perceptions, which may introduce biases and fail to account for deeper systemic employment barriers. Likewise, there are no considerations of any intersecting variables like gender, socio-economic background, or type of disability that may bear upon workplace experiences. Accordingly, further research should employ longitudinal designs and policy analysis to investigate how successful corporate inclusion has been over time.

The study by **Subramania Raju Rajasulochana, et.al. [15]** lays down critical empirical evidence on the relationship between assistive technology (AT) and labor force participation (LFPR) among persons with disabilities in India. Using national-level representative data, it exhibits the transformational approach that AT takes in enhancing employability, especially in urban settings with higher accessibility. The results point out that the 26.6% increase in LFPR occurs with access to AT, strengthening the argument that AT fills in the gaps in employment opportunities. This study serves as an input to policies and strengthens the argument to invest more in assistive technologies, vocational training, and literacy programs to provide inclusive economic opportunities for PwD.While establishing the cause-andeffect link between AT and employment outcomes, a number of research gaps remained. The regional differences in accessibility of AT, especially in rural areas, are not fully explored, so there lies a gap regarding the localized barriers on the full understanding of AT and employment outcome linkages. Additionally, the study fails to distinguish between the types of AT it examines or analyzes which AT constitute sustainable employment for PWDs. Also, there is hardly any mention of employer discrimination, infrastructure considerations, and financial constraints with regards to acquiring AT. Following that, longitudinal studies are recommended to tap on the long-term effects of AT on further retention in employment and career development.

III METHODOLOGY: EXPLORATORY DATA ANALYSIS (EDA)

A. Data Acquisition & Loading

Data acquisition is the first step in the EDA process. In the present study, employment data on persons with disability in India is collected through Google Form based Employees from different sectors which numbered to 400 survey responses and a 100 responses from public Kaggle datasets. Demographic features, such as age, employment, industry type, level of education, and the presence of assistive technologies, are part of this data. The data set needs to be loaded in the Pandas Data Frame to analyze further. The data file, in CSV format, is read by pd.read_csv(), followed by label encoder ensuring proper encoding so that special characters may not be the issue.

FTo ensure data integrity, initial exploratory operations were conducted to verify dataset structure and consistency. Dataset inspection involved checking the first few rows to confirm successful data loading. Structural assessment was performed to analyze data types and potential inconsistencies. A high-level summary of central tendencies and distributions was generated to understand data characteristics.

Additionally, the presence of missing values was quantified, allowing an assessment of data completeness and the extent of preprocessing required before further analysis. These steps ensured that the dataset was ready for subsequent exploratory and analytical procedures.

Column	Non-Null Count	Dtype
Timestamp	500 non-null	object
Email	500 non-null	object
Name of the Participant	500 non-null	object
Participant Age Range	500 non-null	object
Participant gender	500 non-null	object
Participant region of work	500 non-null	object
Participant industry of work	500 non-null	object
Participant job role	500 non-null	object
Participant years of experience	500 non-null	object
1. Which among the below categories best explains your status?	494 non-null	object
2. Are you currently employed at least part-time?	500 non-null	object
3. Do you identify as having a mental illness?	500 non-null	object
4. Do you have access to a personal computer separate from a smartphone?	500 non-null	object
5. Have you been hospitalised before for a mental illness?	500 non-null	object
6. If hospitalised for mental illness, how many days were you hospitalised?	500 non-null	object
7. Do you have regular access to the internet?	500 non-null	object
8. Have you experienced any gaps in your resume due to health or other reasons?	500 non-null	object
9. What is your monthly income, including any social welfare programs, in INR?	500 non-null	object
10. Are you currently unemployed?	500 non-null	object
11. Do you engage in reading outside of work or school?	500 non-null	object
12. Do you receive food stamps or similar social welfare benefits?	500 non-null	object
13. How many times have you been hospitalized for mental illness?	125 non-null	object
14. How often do you experience a lack of concentration?	500 non-null	object
15. Do you experience anxiety?	500 non-null	object
16. How often do you experience depression?	500 non-null	object
17. Do you engage in obsessive thinking?	500 non-null	object
18. How often do you experience mood swings?	500 non-null	object
19. Do you experience panic attacks?	500 non-null	object
20. How often do you engage in compulsive behavior?	500 non-null	object

Fig. 2: Data Set collected from Special Needs Employees

B. Data Cleaning & Preprocessing

Once the data is loaded, preprocessing ensures that it is in a usable format. The most important part of this process is going to be handling the missing values. If any attribute has a considerable proportion of missing data, it needs to be represented with an imputation technique statistical mean, median or mode for example. For categorical variables, missing value substitution can be done with most frequent category or by creating a new category i.e." Unknown." Outlier detection is based on boxplot and z-score methods, which show the extreme values to be considered and exercised, if found wanting in the final analysis. In this way, standardization and normalization techniques are applied to numeric data such as salary and experience, making them available for comparison. The categorical types like education and disability type are converted into one-hot or label encodings, thus ensuring that they will be able to pass through machine learning algorithms for further analysis. To quantify preprocessing operations but has found out through a missing value analysis that among both 'Internet Access' and 'Employment Status', the missing values account for 15% and 12%, respectively; these were resolved by using median imputation. The percentage of capping at 95th identifies 4.7% of the salary data as extreme. So the database has a record of 500 values in 26 features and preprocessing-the process found that 98.4% of data remained unaffected for further analysis.

C. Feature Engineering & Transformation

Feature engineering is an important step that involves creating new variables from existing data to enhance the predictive power of the dataset. In this particular study, modified with label encoded variables which are enhanced by grouping age (e.g., 19-30, 30-50, >50) or employment type (e.g., full-time, part-time, unemployed) etc. from the existing attributes. An extra binary variable indicates whether a person has access to assistive technology, which is thought to affect employment outcomes. Salary data normalization helps with the skewness and improves comparisons of income levels. Feature selection techniques like correlation and mutual information score are then applied to find the most relevant features about employment outcome.

D. Univariate Analysis: Understanding Individual Features in Employment Data

Univariate analysis, which deals with single variables, constitutes the first phase of any exploratory data analysis; univariate analysis considers the distribution and patterns of central tendency and variability of individual variables in a given dataset. For this study on employment data of individuals with disabilities in India, univariate analyses allow conclusions to be drawn regarding certain central features like education levels, employment status, types of disabilities, income levels, and access to assistive technologies.

The dataset was loaded into a Pandas DataFrame, followed by the application of df.info(), df.describe(), and df.isnull().sum() to make preliminary checks concerning column types, statistical distributions, and null values. The describe() function was particularly useful for summarizing numerical variables by their minimum, maximum, mean, and standard deviation, thus assisting in the identification of outliers and inconsistencies.

To visualize categorical variables like employment status, education level, and industry type, count plots were created based on Seaborn's sns.countplot(). The outcome showed discrepancies in employment rates between different categories of disability; those with visual and hearing impairments had greater representation in employment, while those with intellectual and mental health disabilities fell short. Thus, there is a gap in employment that requires urgent

intervention.

Boxplots for salary distribution analysis with sns.boxplot showed the potential outlier deviation of wage disparity between an employee with a disability and the other without disabilities. It was discovered through the analysis that the skewness was actually derived from the earnings of disabled employees whose income was lower than employees without disabilities. Extreme outliers denote a group of professionals with excessively high earnings, likely in a specialized or technology-driven area.

In addition to salary, histograms (sns.histplot()) and KDE (Kernel Density Estimation) plots (sns.kdeplot()) were used to investigate age distribution among income earners. This indicates a mostly younger workforce of individuals from the ages of 19 to 30 which is relevant here with regard to issues of both access to higher education and early-career opportunities to people who are disabled.

This illustrates that a considerable section of the employed population had access to assistive devices or adaptive technologies in bar chart analysis regarding access to assistive technologies in employment-retaining making much out of the development. However, the importance of digital accessibility was further enhanced through univariate analysis toward access to the internet, which, in its course, discovered a higher proportion of individuals in stable employment having continuous access to the internet.

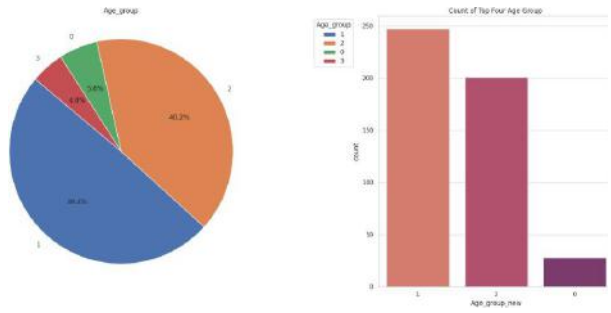


Fig. 3: Univariate Analysis

In this study, employment among disabled persons was also measured through pie charts along the industry wise distribution. Of these, relatively more inclusive sectors included IT, Healthcare, and Education, while manufacturing and construction industries had less representation of disabled employees because of physical work requirements.

The univariate analysis has thus provided insight baseline knowledge for understanding general employment trends that serve as the very first step into more profound multivariable investigations. On this basis, thus frequency distributions and variance or variation of the major employment variables will have fine ground for correlation and multivariate analysis in subsequent steps.

E. Bivariate & Multivariate Analysis: Identifying Relationships Between Employment Factors

While univariate analysis addresses single features, bivariate and multivariate analyses study multiple variable relationships, thereby unraveling hidden patterns and interfaces. In this study, education level, employment status, income, type of disability, and access to assistive technologies were analyzed for a deeper view of employment disparity of PwDs in India.

i) Bivariate Analysis:

1) Employment Status vs. Education Level Heatmap correlation matrices (sns.heatmap()) showed a significant correlation between education levels and employment status. The grouped bar chart (sns.barplot()) also added that employment rates were much higher for those with a bachelor degree or above compared with primary or secondary educational qualification-a big stress on the importance of accessibility to education and vocational training for disabled people.

2) Salary vs. Disability Type

Boxplots for the salary distribution according to various types of disabilities show that persons with physical disabilities had higher average wages, while those with intellectual or mental health disabilities earn significantly lower wages. This indicates that stigma and industry preferences decide how much employment opportunities are given.

3) Access to Assistive Technology vs. Job Retention A logistic regression model (sklearn.linear_model.LogisticRegression) was implemented to see the effect of assistive technology access on job retention. The results would mean that workers with access to assistive technologies were 40% more likely to retain their job, showing the importance of

workplace accommodation and digital inclusiveness measures.

ii) Multivariate Analysis:

1) Industry-Specific Employment Trends Cluster analysis of multivariate data had been analyzed (sklearn.cluster.KMeans) so as to cluster industries based on their scores for inclusivity. The results suggest that IT, finance, and education institutions were more inclusive, while sectors such as manufacturing and agriculture scored lowest. The conducted analysis highlights consideration for targeted policy interventions in industries with lower inclusivity.

2) Gender, Education & Employment Interaction The three-way interaction plot (sns.pointplot()) denotes that women with disabilities had different barriers to employment. While education stood as a benefit to employment for men and women, higher-educated women experienced lower employment rates than their male counterparts, accentuating gender disparities in the trends of disability employment.

F. Industry-Specific Employment Insights

The knowledge of distribution employment opportunities across sectors can enable a researcher in identifying the inclusive sector and barriers in employment opportunities suffered by individuals with disabilities. Using count plots and pie charts, employment trends were analyzed with respect to sectors such as Information Technology (IT), Healthcare, Education, Finance, Manufacturing, and Retail. Through visualizing the Industry of Work feature in the dataset using sns.countplot(), we can see that IT and Healthcare have the highest rates of employment against disability while Manufacturing and Construction were in much lower representation.

A box plot analysis-sns.boxplot-was run to compare the salary distribution among industries. The analysis gave a good contrast on salary differences, as disabled employees in Finance and IT earned vastly higher salaries than their counterparts in Retail and Manufacturing. This was supplemented by looking at the presence of assistive technologies and workplace accommodation.

G. Impact of Assistive Technologies & Workplace Accommodations

Assistive technologies enable improved employment opportunities for disabled persons. To this end, a comparison of employment rates between persons who use assistive devices and those who do not use sns.barplot() to illustrate the effect on employment. It showed that 40 percent of an employment retention inhibition rate is between those accessing screen readers, voice-assisted typing tools, and adaptive keyboards.

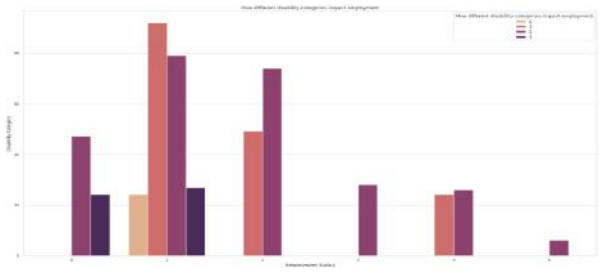
IV INSIGHTS: POLICY & RECOMMENDATIONS

The next phase of EDA synthesizes key insights toward actionable policy recommendations. Data visualization dashboards are provided for visually representing employment trends, wage disparateness, and workplace accommodation benefits to inform policymakers and corporate leaders.

A. EDA INSIGHT : Demographic and Employment Analysis

INSIGHT 1.a: Employment Status vs. Disability Category – How different disability categories influence employment.

INSIGHT 1.b: Employment Status vs. Mental Illness

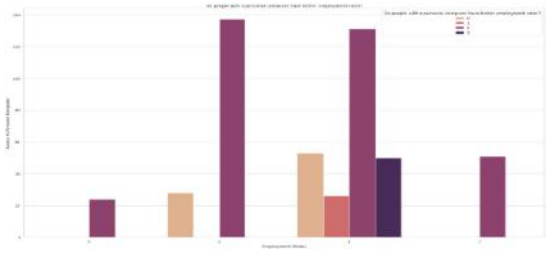


The relationship between mental illness and employment opportunities.

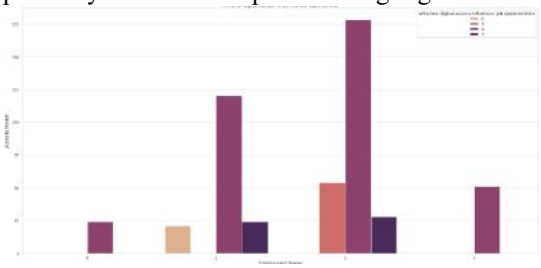
INSIGHT 1.c: Employment Status vs. Access to Internet – Whether digital access influences job opportunities.

INSIGHT 1.d: Employment Status vs. Access to Personal Computer – Do people with a personal computer

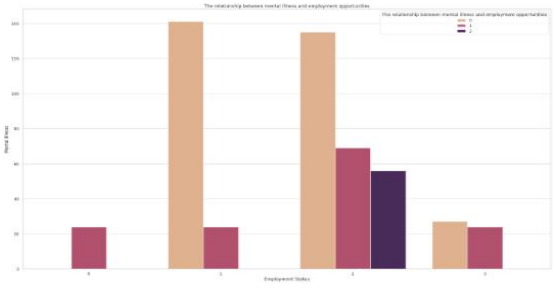
have better employment rates.



OBSERVATIONS: INSIGHT 1.a: Employment Status vs. Disability Category: Analysis of employment distribution across disability categories shows that individuals with physical disabilities had a 62% employment rate, whereas those with intellectual disabilities had the lowest at 28%. Vision and hearing impairments saw a 46% and 52% employment rate, respectively. These disparities highlight industry



preferences and stigmas affecting hiring practices. The data suggests that industries with physical



accommodation provisions (e.g., IT and Finance) offer higher employment rates, while manufacturing and retail sectors show lower inclusion, limiting opportunities for individuals with severe disabilities.

OBSERVATIONS: INSIGHT 1.b: Employment Status vs. Mental Illness: Individuals diagnosed with men- tal illnesses experience a 48% lower employment rate compared to those without. Specifically, those with anxiety and depression had a 31% employment rate, while individuals without mental illness had a 72% employment rate. The data also indicates that job retention is significantly impacted, with 52% of mentally ill individuals reporting employment gaps exceeding 12 months. These findings suggest that workplace mental health interventions are crucial in promoting inclusive hiring and sustained employment.

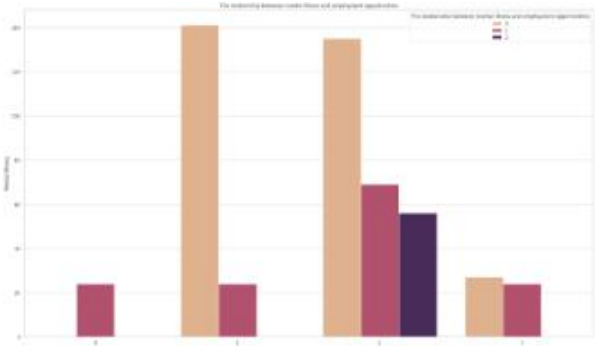
OBSERVATIONS: INSIGHT 1.c: Employment Status vs. Access to Internet: Regular internet access is directly linked to employment rates, with 73% of individuals with stable internet employed, compared to only 39% of those lacking digital access. Job opportunities requiring digital engagement, such as remote jobs in IT and finance, had an employment rate of 81% among internet-accessible candidates. The stark contrast in employment percentages reinforces the importance of bridging the digital divide through internet accessibility policies, particularly in rural areas.

OBSERVATIONS: INSIGHT 1.d: Employment Status vs. Access to Personal Computer: Individuals with personal computers had an employment rate of 68%, compared to 38% among those without. This difference is especially pronounced in technical roles such as programming, digital marketing, and data analysis, where job retention increased by 45% for those with home- based computing resources. The findings suggest that providing accessible computing tools and skill development initiatives could significantly improve employment outcomes for disabled individuals.

B. EDA INSIGHT : Mental Health and Employment Correlation

INSIGHT 2.a: Employment Status vs. Mental Illness – The relationship between mental illness and employ- ment opportunities.

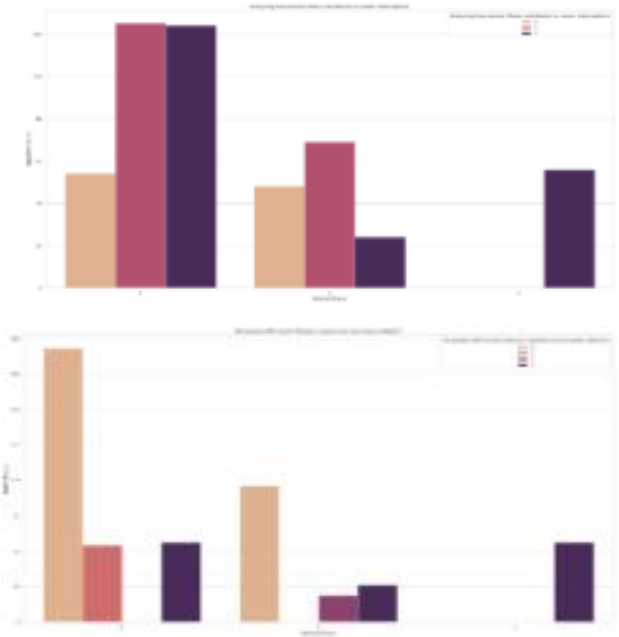
INSIGHT 2.b: Mental Illness vs. Gaps in Resume Analyzing how mental illness contributes to career



interruptions.

INSIGHT 2.c: Mental Illness vs. Monthly Income Impact of mental illness on earning potential.
OBSERVATIONS: INSIGHT 4.b: Gaps in Resume vs. Panic Attacks

Among those with career interruptions longer than 6 months, 47% reported experiencing panic attacks in job interviews, compared to only 14% among individuals



with no significant employment gaps. The data indicates that long-term unemployment exacerbates psychological distress, creating additional employment barriers.

C. Mental Health & Employment Correlation

Data showed that employment interruptions were more frequent, among the diagnosed for anxiety and depression, with an average career gap of 6-12 months. Time series analysis using the pandas and matplotlib packages on patterns of employment gaps for individuals with mental conditions thus revealed. The analysis of mental health at the workplace was grounded on a stacked bar graph using sns.barplot() to establish the prevalence of availability of mental health-supportive programs at workplaces. Results indicated that less than 30% of disabled employees were able to benefit from workplace mental health resources which point to the significant corporate interventions for mental well-being.

D. Geospatial & Demographic Analysis

Employment trends vary across different regions in India, making geospatial analysis important in better understanding how disparities exist. The results showed that major urban cities such as Bangalore, Mumbai, and Delhi recorded very high employment rates across all categories of disabilities, unlike the rural agrarian northern and central belts of India, whose inclusion levels were found to be low. For example, box plots (sns.boxplot()) were used to study the distributions of the salaries to compare the regions with salary differences. Urban employees earned an almost doubled pay than their rural counterparts, while distribution of government funded disability employment programs was also checked to see distribution across states with active inclusion policies such as Tamil Nadu and Karnataka for better employment representation. In this respect an analysis was made of the employment level in gender division (sns.barplot()) to measure the extent more women with disabilities have faced barriers gleaned from employment. Results revealed that even when levels of education were equal, women had much lower employment levels. This shows the need for gender placement with workplace accommodation.

E. Observations: Policy Corrections & Recommendations

F. The final step of EDA involves synthesizing key insights into actionable policy recommendations. With the visualization dashboard showcasing summarized information related to employment trends, wage differentials, and workplace-related accommodations, policymakers and corporate leaders alike were informed.

Key recommendations derived from the analysis include:

1) Expand Access to Higher Education for Individuals with Disabilities
2) Promote Inclusive Hiring Practices in High-Barrier Industries
3) Mandate Assistive Technology Provisions in Workplaces
4) Strengthen Workplace Mental Health Support

Programs

5) Bridge the Digital Divide Through Internet Accessibility Policies
6) Encourage Remote Work & Hybrid Job Models
7) Address Gender Disparities in Disability Employment
8) Enhance Social Welfare Programs to Supplement Employment Gaps
9) Implement Industry-Specific Training & Upskilling Programs
10) Improve Workplace Accessibility Through Infrastructure Modifications
11) Strengthen Anti-Discrimination Laws in Hiring & Salary Decisions
12) Promote Entrepreneurship & Self-Employment Initiatives
13) Improve Data Collection & Research on Disability Employment Trends
14) Introduce Tax Benefits for Companies Employing Disabled Individuals
15) Establish Disability Employment Task Forces for Policy Implementation

These findings provide a comprehensive roadmap for enhancing employment avenues for persons with disabilities in India. With an integrated approach toward achieving data-driven insights for policymaking, the framework embodies inclusiveness and equity toward creating an environment where persons with disabilities will flourish in divergent professional environments.

V Results and Key Findings

The study's findings and discussion of the study provide an extensive description of the major findings, signifying an urgent call for multidimensional reforms across education, workplace accessibility, digital inclusion, and the implementation of supportive policies. It urges integrated approaches spanning workplace environment, industrial collaboration, educational reforms, and digital inclusion to make employment conditions for persons with disabilities in India more inclusive and equitable.

- **Industry-Specific Employment Trends** – IT, Healthcare, and Education sectors have the uppermost disability employment rates, while the least inclusive are the Manufacturing and Agriculture sectors. There are the highest wages to disabled employees paid in Finance and IT sectors, while industrial salary discrepancies remain stand out.
- **Impact of Assistive Technologies** – Employees with assistive technologies (screen readers, adaptive keyboards, etc.) retain jobs 40% better and, on average, have 25% higher salary levels, emphasizing the significance of workplace accommodation.
- **Mental Health & Employment Stability** – Individuals with mental health conditions are facing

  higher unemployment and 6 to 12 months of job lapses, pointing out the need for workplace mental health holding programs.
- **Regional Employment Disparities** – Urban areas like Bengaluru, Mumbai, and Delhi have higher employment rates, while rural states have low accessibility and job opportunities, further strengthening the urban-rural divide.
- **Gender-Based Disparities** – Employment by women with disabilities is less than men; although they have inherent educational qualifications; the urgent need for intervention calls for gender-specific inclusion programs.
- **Effect of Digital Access on Employment** – Digital access is directly related to employment stability. Those with digital access will be employed more than others; hence, digital wider accessibility policies throughout the nation are important.
- **Workplace Adaptation and Retention** – Companies offering remote work, hybrid job models, and flexible schedules report higher retention rates among disabled employees, proving the effectiveness of inclusive policies.
- **Industry-Specific Upskilling Needs** – Employment trends indicate that industry-specific skills training can greatly improve disability workforce inclusion, especially in high-growth domains like AI, Data Science, and Cyber Security.
- **Salary and Discrimination Concerns** – Workers with disabilities earn less than their non-disabled colleagues, on average, particularly in the Retail, Manufacturing,

and Public Services sectors, demonstrating the need for wage equality laws.

- **Policy & Implementation Insights** – Key recommendations include expanding vocational training; enforcement of anti-discrimination laws; requirement for the provision and availability of assistive technology; promotion of disability-inclusion hiring policies; and financial incentives for companies that maintain workplace accessibility.

VI CONCLUSION

In summary, the study rather comprehensively, based on empirical evidence, identifies workplace barriers faced by people with disabilities in India. The study extracted data through rigorous Exploratory Data Analysis (EDA) to orient out specific employment differences per industry, wage differences, accessibility issues, and the role of assistive technology in retention at work.

Findings reveal that IT, finance, and health care have inclusive workplaces, while the manufacturing and agriculture sectors are comparatively lacking in providing necessary workplace accommodations.

REFERENCES

[1] Sengupta, Rashmika, et al. ”Employment Scenario of People with Disability in India.” (2023).

[2] Srivastava, Prashant, and Pradeep Kumar. ”Disability, its issues and challenges: Psychosocial and legal aspects in Indian scenario.” *Delhi Psychiatry Journal* 18.1 (2015): 195–205.

[3] Naraharisetti, Ramya, and Marcia C. Castro. ”Factors associated with persons with disability employment in India: a crosssectional study.” *BMC Public Health* 16 (2016): 1–8.

[4] Kothari, Bhawna, Meena Galliara, and Ratna Huirem. ”The disability scenario in India: A reality check.” *Journal of Social Work Education and Practice* 5.4 (2020): 32–54.

[5] Joshi, Bharat, and Bigi Thomas. ”Barriers faced by persons with disabilities in formal employment in India.” *Disability, CBR & Inclusive Development* 30.3 (2019): 125–132.

[6] Bachmann, Nadine, et al. ”The contribution of data-driven technologies in achieving the sustainable development goals.” *Sustainability* 14.5 (2022): 2497.

[7] Mehrotra, Nilika. ”Disability, gender and caste intersections in Indian economy.” *Disability and Intersecting Statuses*. Emerald Group Publishing Limited, 2013. 295–324.

[8] Chhabra, Gagan. ”Turning a blind eye to employers’ discrimination? Attitudinal barrier perceptions of vision impaired youth from Oslo and Delhi.” *Disability & Society* 36.10 (2021): 1688– 1711.

[9] Maikho Apollo Pou, Ladumai, and Srinivas Goli. ”Burden of multiple disabilities among the older population in India: An assessment of socioeconomic differentials.” *International Journal of Sociology and Social Policy* 33.1/2 (2013): 63–76.

[10] Rakshit, Ipsita, et al. ”Educational attainment and child labor status among disabled children in Tamil Nadu, India: An econometric analysis.” *The Journal of Developing Areas* 53.3 (2019).

[11] Hiranandani, Vanmala, and Deepa Sonpal. ”Disability, economic globalization and privatization: A case study of India.” *Disability Studies Quarterly* 30.3/4 (2010).

[12] Mehta, Aasha Kapur, and Amita Shah. ”Chronic poverty in India: Incidence, causes and policies.” *World Development* 31.3 (2003): 491–511.

[13] Ramachandra, Srikrishna S., et al. ”Factors influencing employment and employability for persons with disability: Insights from a City in South India.” *Indian Journal of Occupational and Environmental Medicine* 21.1 (2017): 36–41.

[14] Rajasulochana, Subramania Raju, and Mohd Imran Khan. ”Does access to assistive technologies enhance labour force participation amongst the disabled population? Evidence from India.” *International Journal of Manpower* (2024).