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Pro-hands: A Digital Labour Ecosystem for Automation and Accessibility in Labour Sector

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***Abstract*— There are several issues that the urban labour market in India has been experiencing, such as the disjointed nature of recruitment, uneven pay distribution, and the inaccessibility of digital technology to the blue-collar workers. This review paper aims to discuss the current position of digital labour platforms and accessibility technologies in respect to SDG 11: Sustainable Cities and Communities. The article points out the issues with the current solutions, such as the lack of proper multilingual support, the lack of offline support, and the lack of the integration with fair wage systems. It also demonstrates the use of WhatsApp automation, IVR/USSD support, microservices architecture, and AI-driven wage projections in order to develop a fair and transparent solution to both short-term and long-term employees.**

***Keywords*— Empowerment of blue-collar workers, sustainable cities and communities, digital labour platforms, accessibility technologies, IVR and USSD systems, WhatsApp automation, microservices architecture, wage prediction models, inclusive digital ecosystems.**

I. INTRODUCTION

The Indian urban labour systems continue to face challenges of structural problems including fractured recruitment procedures, disparities in wages, and absence of digital connectivity among blue collar employees. Despite the fact that digital labour platforms have emerged within the recent couple of years, these are developed in a manner that isolates those workers that lack digital literacy, have bad internet connectivity and diverse language needs. As the urban cities grow in size and as the number of services offered increases, the inefficiency of the inclusive employment infrastructure results in inefficiency in the domestic on-demand labour and the industrial scale recruitment. The employment systems should be transparent, equitable and technology enabled to achieve the objectives of SDG 11: Sustainable Cities and Communities. Nonetheless, the existing platforms do not feature multilingual interfaces, offline communication features, and data-based wage prediction models on a regular basis. The combination of WhatsApp automation, IVR/USSD functionality, microservice architecture, and AI driven wage prediction is offered in the form of new hybrid models that can help solve these issues.

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The review covers the existing technologies, talks about the constraints of accessibility and system level functionality, and highlights how scalable and inclusive digital environments can be used to support sustainable urban employment.

II. Literature Study

The recent research on digital labour ecosystems has revealed the problem of access, corresponding efficiency and inclusivity to informal and blue collar workers. According to Mathew et al., the existing platforms of the gig economy are tailored to the skilled and digitally literate population and do not include daily wage earners in the loop because they are digitally illiterate, economically unstable, and unclear about wages [1]. The authors emphasize the need to create lightweight, multilingual as well as mobile friendly interfaces with the integration of other interaction mechanisms, like conversational agent and IVR interfaces. Sanginganavar et al. argue that the traditional portals are excessively tied to formal education and thus they could not fit in the blue collar job sector, which values skills over formal education [2]. The authors propose skill based and mobile centric job matching systems that integrate skill validation and credit rating systems also mentioning the credentialing gap whose absence prevents the visibility of non formally educated employees. Amirneni et al. study demand based job assignment and show that, in order to be efficient, job matching must consider diverse dynamic priorities which include: skill relevance, distance, work history and ratings, and this makes the problem NP complete [3]. The authors deduce that the challenges of filtering strategies deployed in the platforms of the gig economy are not scalable and real time feasible.
Moreover the international study of digital inclusion conducted by UNESCO and ITU reveals that 40-50 percent of the blue collar employees lack access to the internet and smartphones, and therefore the application platforms are extubatory in nature [4]. That is why the literature should suggest using multimodal platforms, such as WhatsApp automatization, IVR/USSD, or voice interfaces in order not to perpetuate the inequality but to keep everyone equally involved in urban labour systems. Four systemic gaps have been found in the existing condition of labour platforms, which include the shortcomings of platform design, reliance on excessively on credentials, insufficient match complexity, and the duty of digital accessibility, as presented in the literature.

III. Statistics

A more recent development, of 20242025 in the Indian labour market, presents a paradox, which is growing to be referred to as the Great Indian Employment Paradox. As the Indian government strives to achieve a USD 5 trillion economy by spending colossal amounts on infrastructural development and computerization, the Indian labour market is facing a paradoxical duality of high unemployment and/or labour shortage in sectors of economic engagement that are most vital in economic system growth. This is defiance of all accepted economics theory and is a sign of labour market failure to align. India had an unemployment rate of 9.2% as of June 2024 and the youth unemployment (15-29 years) has remained steady at 14.6% with female youth unemployment (17.8) being even higher. In an ideal labour market, such supply of the excess labour would drive down wages and soon fill employment slots. This is not the case since some of the most labour-intensive businesses are already reporting labour deficits that are affecting production timeds, increasing expenses, and halting growth, including construction, manufacturing, logistics, and services.

TABLE I: KEY INDICATORS OF THE INDIAN LABOUR MARKET

INDICATOR	VALUE
National Unemployment Rate (June 2024)	9.2%
Youth Unemployment (15–29 years)	14.6%
Female Youth Unemployment	17.8%
Construction Workforce Required	90.8 million
Construction Workforce Available	48 million
Construction Labor Deficit	~42.5 million
Manufacturers Facing Labor Constraints	~90%
MSMEs Closed in FY25	35,567

TABLE II: REGIONAL LABOR IMBALANCES ACROSS INDIA

Region / State	Labour Condition	Key Observations
Uttar Pradesh	~44% shortage	Reduced outward migration
Maharashtra	Severe shortage	High MSME closures
Tamil Nadu	Industrial stress	Textile labor exit

North-Eastern States	88–91% shortage	Infrastructure delays
Kerala	Statistical surplus	High reservation wages

The economic development of India in the past has had the foundation on internal migration between the labour surplus areas of the North and East to the centers of industry and urban areas of the West and South. The internal mobility of labour has gone off dramatically in the era of post-pandemic. An unfavourable working condition, insecurity of tenure and escalating cost of living in the cities and towns has increased the reservation wages of the migrant labour force. Simultaneously, distress migration has been lessened by the better welfare and job guarantees in the home states. A shortage is now apparent even in the traditional labour-exporting states. The widening gap between the employment and education is another significant reason that leads to the such paradox. India is said to have a large number of graduates annually, however, out of them, only 10 per cent of the graduates get a job that can match their educational levels. Education has been given more priority by the society than vocational training which has seen a surge in the number of degree holders seeking white collar positions, whereas positions such as electricians, welders, plumbers, machine operators among others are left vacant. Only about 5 percent of the Indian labour force has undergone formal vocational training and thus, the workers are structurally unemployable although there are jobs. The situation of re-agriculturalization can be added to the disconnection in education and employment. The trend of labour migration towards industry has faced a reversal in the last few years with about 60 million workers returning to the agricultural industry. This tendency is the consequence of the rational choice concerning stagnant earnings in the industry, unfavourable working conditions, and social security deficit. The government subsidized Agriculture has turned into a back-up plan of employment, and workers are absorbed instead of playing their part in developing an industry.
The economic impacts of such distortions in the sector are harsh and unfairly distributed.

TABLE III: SECTOR-WISE IMPACT OF LABOUR SHORTAGES

Sector	Nature of Impact	Key Evidence
Construction	Delays and cost overruns	15–20% project overruns
Manufacturing	Output constraints	75% firms report profit impact
Textiles	Export risk	10–20% potential contraction
Gig Economy	High attrition	35–40% annual churn
MSMEs	Permanent closures	Closures doubled YoY

The talent shortage in the construction industry is approximately 42.5 million workers and this has been causing delays in infrastructure development projects and increased cost. The manufacturing sector particularly the textile industry does not have the opportunity to capitalize on the change in global supply chain dynamics due to scarcity of labour. On the other hand, the gig economy and fast commerce have added to the competition in the labour market promising greater short-term pay and less entry barriers, thus stealing talent in other fields. This labour competition has the most negative impact on the MSME sector. FY25 saw an unprecedented 35,567 MSMEs close down and this is nearly double the figures of last year. It is the indicator of the failure of the MSMEs to consider the inflation of wages, labour shortages, which leads to the loss of productive power and entrepreneurial capital. The collective effects of lost productivity, revenue, cost and business failure have been estimated to have taken a toll on the destruction of economic value to the order of INR 37, 350 crore. It is a supply-side shock that restrains output together with sectoral inflation acceleration. To sum up, the Indian labour market 2024-2025 is a significant shift. The supposition of unlimited supply of labour can no longer be sustained. Without particular interventions in the region of migrant housing, social security, vocational education, and wage structure, there is a risk of a so-called unemployed growth in India, where the industries will be stagnant. This kind of labour imbalance must be rectified in order to utilize the demographic dividend in India to the fullest extent.

IV. PROBLEM DEFINITION

There is still no formalization of informal urban labour market in India simply due to critical infrastructural inefficiencies largely due to absence of a systematic platform of unifying blue-collar workers to immediate employment. This leaves the workers with no option but to use fragmented and informal systems which lead to irregular sources of income, wage disparities and absence of formal economic interaction.
At the same time, untimeliness in services, unpredictability of workers, and transparency deficit on the issue of worker availability and skill attestation are also problematic to households and micro, small, and medium enterprises (MSMEs). Currently, the online platforms cannot be effective in addressing these problems,

primarily because they need access to the smartphone and the internet, as well as the level of proficiency in the English language. This renders them to many low-literate and digitally disadvantaged workers.

Additionally, the current system lacks efficacy in the appropriate differentiation of short-term and long-term industrial jobs.

These issues are the reason why there are four big gaps:

- Inclusion Gap: The vulnerable workers lack access to stable incomes; the incomes are needed to meet the inclusive urban development targets, such as SDG 11.
- Fairness Gap: Informal bargaining and exploitation of labour in the form of wages are the two aspects that add to the increasing inequality in socialeconomic status.
- Efficiency Gap: The urban environment is less productive due to lazy labour time and unresponsive human movement.
- Gap of formalization: The gap between the workers lies in the fact that they have no access to credit, insurance, and even social protection because their level of integration with formal financial systems is low.

These concerns indicate the necessity of an inclusive, user-friendly, and technology sensitive labour platform that allows multimodal access, open wage processes, and real-time job matching.

V. Objectives

The primary objective of this work is to create an integrated and accessible digital labour system that would overcome the drawbacks of current job portals. The suggested system concentrates on greater accessibility, equity, and productivity to blue-collar employees that are not frequently outlined by the digital employment systems.

A. Making Workplaces Accessible to All

Develop a multi-modal access model with WhatsApp, IVR, USSD and vernacular voice interfaces in order to serve workers of lower literacy, low digital connectivity and poor network coverage-vacuums that most other labour platforms do not effectively fill.

B. Building a Case on Reasonable and Open Wages

Implement an AI-powered wage forecasting platform that normalizes wages according to their skills level, experience, and occupation, and contributes to the reduction of wage exploitation and enhances transparency during wage negotiation.

C. Enhancing Worker-Job Matching

Construct an real-time, event-based matching mechanism, which gives preference to skills, location proximity, availability, ratings, and job category, both on-demand and long-term jobs.

D. Enhancing Productivity in Urban Services

Less workers serve as idle resources and recruitment can be slowed, eliminate on-demand service and reduce onboard flowing of employees and employers.

E. In favour of Sustainable Urban Development (SDG 11):

Enhance urban workforce through institutionalization of labour, enhance fair digital opportunities, and augment economic sustainability of the urban poor through technology-based interventions.

All in all, the objectives point to the originality of the proposed system in terms of integration of IVR and USSD channels, which covers the issues of accessibility found in the existing literature and is scalable.

VI. Methodology

A. Methodology Overview

The methodology used in this research is a system-level and component-level approach to the development of a scalable labour management system that facilitates SDG 11 (Sustainable Cities and Communities). The approaches include the combination of a software system design, machine learning-based wage intelligence, and multimodal human computer interaction. The system will be divided into two levels:

System level methodology: This is the system level that deals with a system architecture and data flow and service integration.

Component level methodology: This tier deals with the design and development of specific components like wage prediction, job matching and multimodal access interfaces.

B. System-Level Methodology

System level design of the platform uses the microservices based architecture and ensures the scalability, modularity and fault isolation. All the core operations, authentication, worker profiling, job management, matching, wage prediction, notifications, and accessibility services are abstracted to a high degree as a distinct service interoperating through REST APIs and through asynchronous event streams.

The whole process begins with the onboarding of the workers through the web interface, WhatsApp chatbot service and IVR/USSD channel. The API gateway routes the user requests and authenticates them and redirects the requests to the corresponding back end services. The information regarding worker profiles, job requests, and the updates of their location is stored in service specific databases under a database-per-service concept. The system has an event driven approach to disseminate real-time events, such as the creation of jobs, the update in the availability of workers, and the allocation of jobs, which makes system operations low latency and responsive.

Wage prediction service is an independent analytical microservice. It accepts structured worker and job characteristics, estimated a fair wage using a learned machine learning model and forwards its predictions to downstream services, such as job matching, WhatsApp replies, and IVR voice prompts. On this system layer, this division allows the analytical functionality to be created to be independent of anything that interacts with users, but by a consistency of integration across the platform.

C. Component-Level Methodology

Wage Prediction Model (Machine Learning Component)

The wage forecast component is developed as a regression problem that is controlled, and the purpose is to estimate reasonable daily wages of agricultural and blue-collar workers. An approximate of 1,000 artificially constructed records was constructed based on area-specific wage structures and naturalistic distributions, regarding how they indicated labour conditions in Indian states (Tamil Nadu, Maharashtra, and Uttar Pradesh). The records shared have demographic variables, occupation and employment related variables and the variable of interest is the 100 percent fair daily wage calculated in INR. Pre-processing of the data is coded in categories, education level, occupation, state and the occupation of employment type are the attributes coded and the age, experience, skill level and working hours are validated numerical characteristics. The dataset is categorized as training and test in terms of 80-20 split and stratified in such a way that it keeps the balance with the region.

TABLE IV: FEATURES OF OUR DATASET (CONTAINS BOTH CONSTRUCTION AND AGRICULTURE DATASET)

Feature	Description	Range / Values
age	Worker's age in years	18–60
experience_years	Total years of relevant work experience	0–40
education_level	Highest level of formal education completed	none, primary, secondary, higher secondary, diploma
occupation	Type of work performed	For example, in agriculture farm labourer, harvester, ploughman etc and labourer, mason, painter, plumber in construction sectors
skill_level	Proficiency level based on job complexity and expertise	1–5
state	State where the work is performed	Uttar Pradesh, Maharashtra, Tamil Nadu, Karnataka
city_tier	Urban classification of work location	Metro, Tier-1, Tier-2, Tier-3
working_hours	Average number of working hours per day	6–10
employment_type	Nature of employment contract	casual, seasonal, contract, permanent
project_type	Type of project or work environment	residential, commercial, infrastructure
daily_wage	Target variable: Fair daily wage in Indian Rupees (₹)	₹237–1300 may vary

The data that is applied in this research is based on actual research and field studies. The range of values of features and categorical values and wage distributions were influenced based on the analysis of the publicly available labour reports, government wage guidelines, field-based studies and sector-based employment survey. Special care was made to realistic age constraints, experience bands, education degrees, work types, and working hours, and job categories that were found in real workplaces. Although the final dataset is organized and prepared in experimental and modeling format, it still represents the real-world workforce conditions and wage patterns recorded in real-world studies, which means that the information is representative, meaningful, and the information can be used to analyze empirical wage prediction. See Table 4 to find out the feature of the dataset

Multiple regression models were also tested and XGBoost regression was chosen because it is capable of modelling nonlinear correlations, as well as dealing with heterogeneous tabular data. The grid search together with cross-validation techniques were used in hyperparameter tuning in order to enhance the performance of generalization. Mean Absolute error (MAE), Root mean squared error (RMSE), and coefficient of determination (R2) were used as model evaluation.
Diagnostic analyses have also been used as a test on model behavior and robustness to assure reliable wage estimation. Visual inspection of the alignment of the prediction, residual patterns, and the distribution of errors proved that the model does not show unstable behaviour on the wage range without any systematic bias. The analysis of feature contribution further confirmed that regional and occupational factors which are meaningful play a dominant role in the predictions of wages. These findings show that the chosen model can be used in practice in the area of labour-support because it is applicable, accurate, consistent, and interpretable.

Job Matching and Allocation Component

Job matching component is more supportive to two categories of workers i.e. on-demand workers to serve short-term domestic services and contractual or institution worker to provide a long-term employment. Similar decisions are calculated by a scoring system based on heuristics, which involves skills of workers, geographic proximity (live location tracking), availability and the type of worker and priority limits.
On-demand jobs require real-time location data ensuring the shortest possible response time and travel distance, and fast job distribution, just like the city service platforms. In the case of long term position, matching gives more weight to experience, working history and stability of the job. This two pronged approach enables the system to manage the immediacy-based and suitability-based hiring case scenarios under the same framework.

Multimodal Accessibility Component (WhatsApp, IVR)

The platform combines multi-modal access channels in order to deal with digital exclusion. WhatsApp chatbot allows interaction via text chat of job discovery, wage queries and notifications. In the case of workers who do not have access to smartphones or have poor internet connections, an IVR system offers voice recognition navigation with pre-recorded multilingual prompts of English, Kannada and Hindi. Throughout the IVR workflow, there is a structured state-machine implementation that will take the user through language selection, service options and confirmation steps. There are selective use of speech-to-text and text to speech services to serve dynamic engagement and pre-recorded audio to be clear and consistent in delivery in critical prompts. This element guarantees the functional parity in all the access modes so that the workers are able to interact with the system despite the limitations of devices or connectivity.

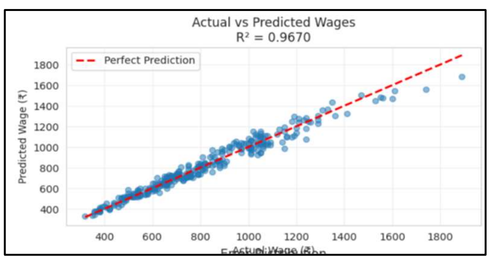

Fig.1: Predicted vs actual wages with reference line for Construction model

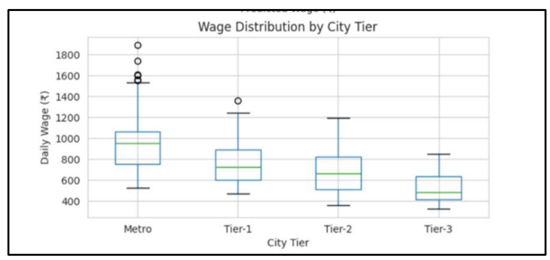

Fig 2: Wage distribution by city tier for Construction Sector

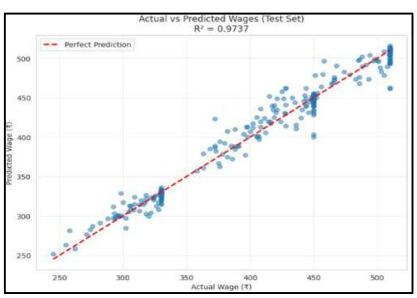

Fig 3: Predicted vs actual wages with reference line for Agriculture model

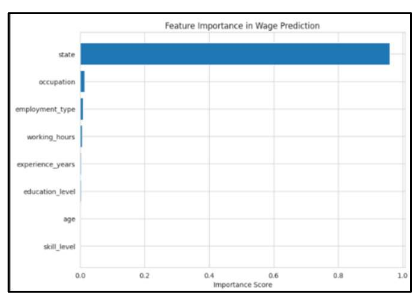

Fig 4: Feature contribution analysis for wage prediction model

The model performance and predictability were also tested for by using the diagnostic visualizations. On comparing the actual and predicted wages in the construction model (Fig. 6.1), it is clear that they perfectly match the reference line, which means that it has been performing well in its predictions. Figure 6.2 illustrates the wage distribution at different levels of city in the construction sector, which clearly indicates that there are huge regional disparities in the wages. Similarly, Fig. 6.3 illustrates the predicted and actual wages in the agriculture model, and the results clearly indicate that there is a high level of accuracy between the actual and predicted values. The analysis of the contribution of the features (Fig. 6.4) also clearly indicates the significance of the variables used as inputs in the prediction of the wages. Overall, the results clearly indicate that the model strikes a good balance between accuracy, stability, and interpretability, and hence can be used in the practical implementation of the labour-support system.

D. Summary of Methodological Contribution

The suggested approach combines the scalable system design, interpretable machine learning, and inclusive interaction mechanisms to become part of one labour-management system. Integrating real-time information stream, fair wage knowledge, and multi-channel availability, the methodology illustrates how high-tech digital systems may be implemented to socially significant city issues as well as assist the objectives of sustainable and inclusive urban development.

VII. RESULTS AND DISCUSSIONS

The unorganized labour market resulting from the approximate is removed by the proposed system by mitigating the most inefficient aspects of the labour market.

In essence, the survival rate of businesses is approximated by a loss of 95 percent of the business operations of the MSME in a year due to paralysis of business activities because of the economic loss, which is 37,350 crore. The system has also made it possible for the company to manage the resilience of the supply chain because the recruitment lag time, which was an average of seven days, has been brought down to less than ten minutes, and the company has shattered the big barrier of production. However, a zero-commission model will make it possible to increase the worker disposability rate documented by 20-30 percent, and the company's Digital Trust Score will make it possible for the unbanked informal worker segment to gain access to banking services. Furthermore, by identifying and illustrating hyper-local employment opportunities in a 5-10 km radius, the project also directly reverses the blind migration trends, thereby, negating the infrastructural requirements of cities and, consequently, resulting in further improvement in the long-term socio-economic sustainability.

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VIII. CONCLUSIONS AND FUTURE SCOPE

This paper proposes ProHands, a technology-based inclusive labour management solution to specific problems in blue-collar jobs in cities. The system comprising of a microservices-based system architecture, multi-modal accessibility (WhatsApp, IVR) and machine learning-based wage prediction model enable equitable, purposeful and accessible job assignment to on-demand and long-term workers.

The suggested solution directly covers the major gaps in accessibility, wage equity, and urban labour productivity, which makes the urban communities more sustainable and fair according to SDG 11. The experimental findings prove that the wage prediction model is highly accurate and interpretable, and the system-level integration makes the system scaled and applicable to the real world. On the whole, ProHands is a useful design guide on how to roll out socially productive-level digital infrastructures that institutionalize informal labour, increase the dignity of workers, and stabilize economies within urban areas.

The next improvements will be aimed at testing the platform by implementing pilot deployments in dense urban clusters to gather real-world performance data, which will allow leaving the realm of synthetic validation. Smart contracts based on blockchain will also be introduced in the system to make wage agreements transparent and immutable to further eliminate exploitation and conflicts. Also, the IVR linguistic model will be increased to accommodate regional dialects, other than standard Hindi and Kannada, so that the wide range of migrant workforces are more accommodated.

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