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From Degrees to Jobs: Modeling Employment Prospects of Postgraduates in India through Machine Learning

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Abstract

The higher education sector of India has experienced fast growth which results in yearly production of millions of postgraduate students. Academic qualifications do not ensure employment opportunities because employability continues to be a major issue in the job market. The labor market faces uncertainty because of this mismatch which threatens the successful utilization of the nation's demographic dividend.

The research creates a predictive system to evaluate postgraduate employability through logistic regression modeling as a machine learning algorithm. The researchers obtained their data by recording academic performance through CGPA scores and experiential learning activities including internships and projects and soft skills such as communication and adaptability and teamwork and institutional support through placement services and recruiter engagement and demographic characteristics of gender and rural–urban background. The model received validation through GNU Octave after preprocessing and feature selection by using accuracy and precision and recall and F1-score. The analysis used odds ratios in combination with feature attribution methods to improve model interpretability. Research shows that employability consists of various elements which work together as a system. Academic achievement remains important but experiential learning and soft skills hold greater value for success because educational institutions offer necessary support systems. The employment results are influenced by two main demographic factors which include rural-urban differences and gender-based inequalities. Research findings indicate that educational organizations need to create a total system transformation to meet current job market demands.

The model generates major economic and social impacts. The economy benefits from higher employability because it drives up aggregate demand which leads to GDP expansion and productivity growth and generates more government income. The social benefits of employment include reduced poverty rates and improved well-being and increased social inclusion. The predictive model helps students and institutions and policymakers by offering specific guidance to lower employment uncertainty. The research provides a solid base although it faces three main constraints from using logistic regression and self-reported skill data and data that only applies to one region. The data-driven approach between education and employment outcomes enables the development of policies and academic practices and labor market efficiency which leads to sustainable and inclusive growth in India.

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1. Introduction

The labor market of India operates as one of the world's most intricate and active employment systems because of its population growth and industrial transformation and changing business requirements. With more than 65% of its population under the age of 35, India possesses an enormous potential workforce that can be harnessed to drive economic growth. The problems of joblessness and insufficient employment and skills not matching available work continue to affect the labor market (NITI Aayog, 2023). Every year educational institutions send millions of graduates into the world but many of these graduates face unemployment or work in positions that do not match their academic qualifications. Postgraduate students need to fulfill more demanding job expectations yet they find it difficult to convert their academic achievements into career roles.

The Indian higher education system operates as the world's second-largest system through its 1000 universities and 42,000 colleges which serve millions of students. The educational pool of the country receives significant contributions from institutions based in tier-II and tier-III cities which include Ranchi and its surrounding regions. The increasing number of postgraduate programs creates an issue because they do not provide adequate training for industrial needs (Agarwal, 2022).The academic-industrial divide results in a talent shortage which enables postgraduate students to study theoretical concepts but prevents them from acquiring practical skills needed for business achievement. Academic qualifications fail to determine employability because several elements including cognitive abilities and behavioral attributes and technical competencies and social capital affect it (Yorke, 2006; Singh & Narayan, 2021). Students who develop communication skills and adaptability and leadership abilities and teamwork skills and problem-solving abilities and professional networking skills will have better employment opportunities. The employment situation becomes more complex because of additional demographic elements which include regional origins and family financial status and job placement accessibility. A complete employability assessment needs an advanced system which goes beyond the evaluation of academic qualifications.

Machine learning (ML) operates as the core analytical tool which processes intricate high-dimensional datasets that feature complex non-linear relationships between variables. Logistic regression functions as a basic statistical learning technique for binary classification tasks which enables the prediction of employment outcomes according to Hosmer et al. 2013).The researchers use logistic regression models to analyze student data for job opportunity prediction and factor identification in these predictions. The evaluation of interaction terms with mediation effects helps researchers understand how different variables work together to either boost or decrease job readiness.

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The choice of Ranchi and its surrounding academic institutions for this study is significant. Ranchi serves as an educational center in Jharkhand which provides academic opportunities to students from various social economic levels. The national discussion about employability centers on top metropolitan universities yet lower-tier institutions provide vital information about India's workforce structure. Students at Ranchi encounter multiple difficulties because they lack industrial experience and their placement system remains underdeveloped and they lack professional connections compared to urban students (Kumar, 2021).The research provides both regional data and general knowledge about Indian higher education that can be applied to the entire system.

Students who enroll in postgraduate programs face an uncertain situation because they spend multiple years and large amounts of money on education without knowing what their future job opportunities will be. The India Skills Report from 2022 shows that about 50% of Indian graduates lack necessary skills which makes them unemployable. Students at the postgraduate level need to link their academic understanding to professional standards yet many students struggle to fulfill industry expectations. The situation becomes worse because of economic instability and irregular employment practices and worldwide changes in the job market caused by automation and artificial intelligence. The situation demands predictive models which will predict job market chances to help both policy makers and educational institutions and their students.

The current methods for assessing employability depend on surveys and expert judgments and academic grades which fail to measure the complex relationship between different skills. The data-driven method of predictive modeling helps researchers identify complex patterns between technical courses and internships and extracurricular activities and networking opportunities. The analysis of employability determinants becomes possible through logistic regression models that include polynomial terms and interaction effects for determining mediation and moderation effects. The models can help universities transform their curricula while students use them to detect their weaknesses and policy makers use them to connect between institutional weaknesses.

Employment prediction models generate economic and social impacts in addition to their academic research applications. The program fights unemployment by implementing two essential methods which help people find work faster and get the most out of their current employment. Early detection of skill deficiencies allows for specific training programs that connect student competencies to industrial requirements which drives national productivity growth. The social impact of employment results in poverty reduction and social mobility improvement and regional development growth. The employment prediction system will help Ranchi students who come from lower-income families by creating specific support programs that promote social development.

The research uses a logistic regression machine learning model to evaluate postgraduate student information from Ranchi and its neighboring educational facilities. The dataset contains 2040 records which include 18 essential features that measure academic performance and behavioral patterns and demographic characteristics. The analysis of training data through model application to new student profiles enables the study to forecast employment results and deliver detailed information about base contributions and mediation and moderation effects. The research aims to

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connect the current knowledge gap through its development of a precise mathematical system which addresses postgraduate employment needs in India.

1.1 Problem Statement

The Indian higher education system stands at a vital point in its ongoing development process. The university faces a major problem because its fast growth in student numbers and facilities does not translate into better job prospects for its graduates who hold postgraduate degrees. Students and their families continue to spend more money on postgraduate education despite the fact that this investment no longer leads to stable employment opportunities. The present situation demands immediate investigation into the reason why Indian students who obtain advanced degrees cannot find employment that corresponds to their qualifications.

Several factors contribute to this issue. Students encounter a long-standing issue because their academic learning at school fails to align with the actual requirements of their future work roles. Universities focus on teaching theoretical concepts but students need to acquire practical skills and solve technical problems for industrial success. Students face difficulties when moving from education to employment because they cannot meet the requirements of their jobs. Second, there is a large distinction between the various geographic areas. Tier-I metropolitan institution graduates perform better because they have network access and placement cell structures yet students from tier-II and tier-III cities including Ranchi encounter limited access to similar career prospects. The present regional gap makes it difficult for people to find existing job openings.

Employability exists as a complex concept which depends on academic achievements together with soft skills and communication abilities and adaptability and social connections. Most traditional methods of employability assessment do not effectively measure these various characteristics. Students who achieve academic success yet lack professional networking skills and adaptability face difficulties when entering the job market. The employment market faces additional challenges because of various economic factors which include unstable labor market conditions and technological changes and worldwide emergencies that create difficulties for postgraduate students to find stable employment.

The current methods used to evaluate employability including surveys and subjective evaluations and basic statistical averages fail to meet the requirements of this situation. The models do not consider the complex relationships between different elements which shape employment results. Predictive modeling provides a better solution which helps to find important features and their impact on employability. The statistical model of logistic regression allows researchers to analyze binary employment status (employed or unemployed) and examine how different variables affect each other through mediation and moderation effects.

The current research lacks predictive models that match the needs of Indian postgraduate students particularly in Ranchi and other similar areas. The absence of dependable data-based frameworks creates confusion for students about their job readiness while institutions face challenges to update their programs and policymakers cannot develop solutions for existing system problems. The main

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issue this research investigates is the absence of complete predictive models which show employment results for Indian postgraduates while offering specific recommendations for each feature. The problem creates obstacles for personal career development while blocking India from achieving its target of using its population growth to drive sustainable economic expansion.

1.2 Formulation of Research Objectives and Hypotheses

The research objectives and hypotheses of this study developed through a systematic process which united the problem statement with existing literature and the acknowledged research gap. As outlined in the introduction and problem statement, the central challenge for postgraduate students in India is the paradox of educational expansion without a proportionate increase in employability. The educational system focuses on developing specialized knowledge but employers doubt that graduates possess the necessary skills for employment because they lack practical experience and soft skills. The research objectives and hypotheses were designed to study employability through its various dimensions which include academic success and behavioral characteristics and individual characteristics.

Grounding in the Problem Statement

The problem statement showed two crucial results.

The first point states that postgraduate education does not lead to employment because students face multiple barriers to employment.

The research identifies two main causes of the skills gap between education and employment which stem from individual factors such as skills and adaptability and communication abilities and from systemic factors including industry relevance and placement opportunities.

The research objective number one aimed to establish which academic factors combined with behavioral elements and demographic variables influence employability. The research hypothesis (H_1) investigated how these features work together to establish their ability to predict employment results.

Literature Review and Research Gap Alignment

Research studies about employability in India focus mainly on academic success and particular skills yet they fail to consider how various factors interact with one another. Social science domains of employability fail to fully adopt predictive modeling with machine learning technology. The study revealed an important research need to combine machine learning methods with social economic and educational data for complete evaluation.

The research gap needed the creation of a predictive model through logistic regression analysis with polynomial and interaction terms to achieve the second research objective. The research

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tested the hypothesis (H_2) to verify that the model generated statistically important predictions which would validate computational approaches for addressing social science problems.

Economic and Social Implication Focus

The third layer of reasoning for the objectives was derived from the study's relevance to policy and practice. The Indian economy encounters two significant problems because graduate unemployment leads to wasted human capital and decreased economic performance. The stakeholders who consist of students and educational institutions and policymakers require functional information to create their intervention plans.

The third research objective received guidance to investigate the extensive economic and social effects predictive modeling generates for employment readiness. The research hypothesis (H_3) aimed to determine that these models would generate practical solutions to decrease employment uncertainty and match curricula to industry needs and boost economic performance.

Logical Flow from General to Specific

The research objectives followed a specific order starting with exploratory work to identify factors then moving to methodological work for model development and finally reaching applicative work for policy and societal impact assessment. The following sequence of logical steps appears in each hypothesis:

The H_1 section shows that features create connections which impact employability whereas, H_2 validates the robustness and accuracy of the predictive model.

The third section of the paper expands the investigation to include effects at the social level. The research follows a logical sequence which starts with theoretical development before moving to empirical verification and concluding with policy implementation.

Ensuring Testability and Relevance

The researchers designed each hypothesis to be verified through the available data of 2040 postgraduate students which met statistical requirements. They are neither overly broad (which would make them untestable) nor overly narrow (which would limit their contribution). The programs establish academic knowledge and practical skills which meet the requirements of both applied economics research and educational needs.

2. Literature Review

The recovery of Indian graduate employability since 2020 has shown inconsistent patterns between Tier-2 and Tier-3 cities in Jharkhand and major urban areas regarding recruiter numbers and job market absorption. The India Skills Report 2024 shows employers choose candidates by evaluating both their soft skills and domain-specific knowledge but the Periodic Labour Force Survey (2023–

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24) shows employment rates vary between different states (Wheebox et al. 2024; Government of India, 2024).The patterns follow the National Education Policy 2020 which established industry alignment and experiential learning as fundamental principles for employability reform (Ministry of Education, 2020).

The academic field after 2020 made soft skills its main priority. Research conducted by recruiters and academic studies demonstrates that graduate hiring success depends equally on technical skills and five essential soft skills which include communication and teamwork and adaptability and leadership and problem-solving (Wheebox et al. 2024; Panakaje et al.,2024).The competencies impact postgraduate students during group discussions and personal interviews because employers conduct these events to determine their readiness for professional work settings. The research findings of Jain, Khare and Gourisaria (2021) confirm that soft skills create a connection between academic achievement and professional readiness in the workplace.

Internships provide the most accurate indication of what a person will do in their future career. The AICTE introduced an internship policy in 2021 which includes experiential training because research shows that such experiences demonstrate student commitment and develop vital industry competencies. The research conducted by ISR 2024 together with empirical studies shows that virtual internships during COVID-19 successfully minimized the experience gap which new graduates faced (Molla et al. 2024).

The institutional ecosystem for campus placements functions at the same level of importance. Recent studies demonstrate how recruiter engagement, alumni involvement, and pre-placement training systematically shape employability outcomes. Rajesh (2022) and Molla et al. (2024) demonstrated that predictive modeling of placement results showed placement cell activities to be the primary factor that affects outcomes according to Panakaje et al. (The 2024 study revealed that students base their college selection on institutional placement records according to the research findings. The research indicates that personal initiative and organizational support create the foundation for employability.

The value of technical skills and certifications has increased because the time it takes for technical abilities to become outdated continues to decrease. According to NASSCOM and BCG (2021) reports data analytics and AI and cloud and cybersecurity skills become outdated quickly which requires graduates to constantly learn new skills to stay employable. Employers in the ISR 2024 data base their assessment of candidates on technical skills demonstrated through certifications and particular abilities yet they continue to consider academic achievements as additional evaluation criteria.

Networking activities together with extracurricular activities create separate benefits that help students prepare for their careers. Research conducted since 2020 shows that students who join LinkedIn professional networks and participate in extracurricular activities obtain better interview results and improved job market success (Panakaje et al. 2024; Wheebox et al.,2024).The experiences show leadership potential through teamwork and adaptability which helps minimize the effects of technical skills.

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The process of determining the best approach to allocate resources between different groups faces challenges related to fairness because demographic characteristics influence these decisions. The PLFS (2023–24) demonstrates that women along with graduates from smaller towns encounter ongoing employment difficulties because of current gender and regional disparities (Government of India, 2024). The practice of adding demographic data to improve predictive accuracy as recommended by interpretable machine learning experts leads to bias continuation in the system which fairness audits serve as a necessary solution (Molnar, 2023).

Scientists began using machine learning approaches for employment potential forecasting through new methods which started in 2020. Rajesh (2022) and Molla et al. (2024) and Rao et al. (The authors applied classification algorithms including logistic regression and decision trees and neural networks to placement data in 2025. The study revealed that although advanced methods occasionally achieve better accuracy than logistic regression the model's clear results make it more suitable for institutional choices. Feature engineering and interaction modeling were found to contribute more to model performance than the choice of algorithm.

Research findings from recent methodological studies show that analysis needs to incorporate non-linear effects together with interaction terms. Nzekwe et al. (2024) and Tian et al. (2022) demonstrate that polynomial and interaction terms reveal concealed relationships between predictors and outcomes according to Levy et al. (The authors in (2020) recommend using logistic regression for these tasks because it provides easy-to-understand results. The inclusion of numerous interaction terms in penalized models such as LASSO or SCAD becomes beneficial according to the results because it helps prevent overfitting.

Thresholding and evaluation function as essential elements within the process. The selection of cut-off values for training accuracy in campus placement studies remains common practice although thresholding literature supports using ROC/PR-based criteria including Youden's J and F1-optimization for cut-off selection (Flach, 2020). Decision-makers achieve their best results through dependable information so organizations should present multiple performance indicators which include AUC and precision-recall and calibration according to Wheebox et al. (2024).

The model provides this capability through its ability to connect coefficients directly to specific feature values which can be used to generate individualized feedback for students and placement cells. Molnar (2023) and Levy et al. (The authors (2020) suggest using interpretable methods in situations where transparency and actionability matter more than the potential accuracy benefits of black-box models.

2.1 Research Gap

The current body of research has grown but multiple domains require additional research according to researchers. The majority of existing research investigates national employment data and engineering undergraduate students yet fails to study postgraduate employment in eastern India. Most models fail to combine multiple variables such as soft skills and internships and technical abilities and networking and demographic factors into one predictive system and none use

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polynomial and interaction-rich logistic models to model non-linear effects. Most studies report predictive accuracy but they do not offer student-level attributions which would be useful for counseling purposes. The current thresholding practices do not meet proper standards while demographic fairness issues remain under addressed. Finally, little attention has been given to documenting pipelines built on low-cost, open-source tools such as GNU Octave, which are critical for resource-constrained public institutions.

The research aims to establish a complete predictive system for postgraduate employability that uses a clear logistic regression model which includes polynomial and interaction variables to address current knowledge deficiencies. The research advances methodological approaches while creating practical student-specific data to boost employability in Jharkhand and similar educational environments.

3. Methodology

The research design uses quantitative predictive-analytical approaches to create forecasting models in machine learning which predict postgraduate student employment results in Jharkhand. The research uses logistic regression as its main analytical tool which includes polynomial and interaction terms to analyze non-linear relationships between variables. The researchers chose logistic regression over complex models like random forests and neural networks because it produces results that can be understood and generates student-specific attribution scores. The system features match educational needs because they provide institutions and students with useful information and precise prediction capabilities.

The research subjects include postgraduate students who attend universities and colleges throughout Jharkhand while studying management economics and commerce at central universities and state universities and private institutions. The research used purposive sampling to achieve institutional diversity before applying stratified random sampling methods that produced participants from different gender groups and social classes and urban and rural areas. The final dataset contained 2040 student records that fulfilled the necessary requirement of having at least 10 to15 observations for each predictor variable in logistic regression.

Data for the study was drawn from multiple complementary sources. The researchers obtained institutional records to track academic performance indicators which included CGPA scores, technical certifications and placement results. The researchers used structured student surveys to evaluate soft skills through assessments of communication abilities and teamwork skills and adaptability and leadership and problem-solving competencies and student self-assessments of their networking activities and their involvement in extracurricular activities. The Placement cell reports served as documentation tools to track internship activities and recruiter interactions and pre-placement training program attendance. The research collected demographic information about gender and social economic status and urban-rural background to study current structural inequalities. The survey instrument reliability assessment used Cronbach’s alpha which produced results above 0.7 thus confirming internal consistency.

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The dependent variable in the model is employability, measured as a binary outcome of employed or unemployed. The independent variables consist of academic performance together with experiential learning elements like internships and projects and self-assessed soft skills and institutional placement support and networking opportunities and participation in extracurricular activities and individual demographic information. Polynomial transformations were applied to continuous variables such as CGPA and internship duration to capture non-linear relationships, while interaction terms, such as those between CGPA and internship experience or communication skills and placement support, were included to account for combined effects that influence employability.

The model was implemented in GNU Octave, an open-source computational platform. The preprocessing process required two operations which included data imputation through mean and mode value replacement and categorical variable conversion to dummy codes and continuous predictor normalization for data consistency. Data was then partitioned into training and testing sets in a 70:30 ratio using stratified sampling to preserve the distribution of the dependent variable. The logistic regression model contained both polynomial and theoretically justified interaction terms according to the model specification.

The researchers applied LASSO regression as a regularization method to stop overfitting because the model included multiple predictors and interaction terms.

The evaluation of model performance required several assessment metrics. The evaluation metrics consisted of overall accuracy but the primary emphasis was on precision and recall and F1-score to obtain balanced performance in cases with class imbalance. The analysis conducted 1,000 bootstrap resamples to create regression coefficient confidence intervals which helped reduce sampling bias for testing robustness and stability.

The research contains interpretability as its main characteristic. The logistic regression coefficients received odds ratio transformation which enabled researchers to understand the strength of each predictor variable. The research investigated which student characteristics most impact the evaluation of employability potential for students at an individual level. The researchers used interaction term analysis to detect both moderating and mediating effects which helped them better understand how institutional elements affect academic and soft-skill variable values. The gathered information helps educational organizations develop better programs for employability training and enables them to offer career guidance to their students.

The research design included vital ethical elements which served as its base structure. Ethical approval was obtained from the institutional review board prior to data collection. All participants gave their free consent to participate in the survey and researchers obtained their informed consent before starting the study. The researchers-maintained data confidentiality through record anonymization while including demographic information to analyze fairness and discrimination without creating discriminatory predictions.

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The research methodology demonstrates both high methodological strength and clear research procedures but it has some limitations. The results from logistic regression are easy to understand but the model does not match the predictive power of more complex machine learning techniques. Self-reported survey assessments of soft skills can lead to biased evaluation outcomes. The research limitations stem from its exclusive focus on Jharkhand which prevents generalization of findings to other states or different contexts. The research maintains its findings about both policymakers and institutions and students because of its robust sampling approach and thorough data collection and interpretability focus.

The features adopted in the building of the employment prediction model has been presented in Table 1. The table shows a structured arrangement of all variables which form the employability prediction model. The model groups predictors into academic, experiential, soft skills, institutional, networking, extracurricular and demographic categories. The model includes variables which have their own specific types that determine their expected impact on employability results. The framework helps explain why specific variables were chosen and it simplifies the interpretation of the logistic regression model.

3.1 Flow of the research

Fig 1 reports the flow of the study. The research starts with data acquisition from institutional records and surveys and placement reports which leads to preprocessing and variable selection according to the flowchart. It then highlights the logistic regression model-building process in GNU Octave, incorporating polynomial and interaction terms.

Table 1: Variables in Employment Prediction

Variable Category	Variable Name	Type	Description	Expected Influence
Academic	CGPA	Continuous	Overall grade point average, normalized for scale differences	Positive
Academic	Technical Certifications	Binary/Count	Professional/industry certifications acquired beyond coursework	Positive
Experiential	Internship Experience	Binary + Continuous	Presence and duration of internships	Strong positive
Experiential	Industry Projects	Binary	Participation in industry/research projects	Positive
Soft Skills	Communication Skills	Ordinal (Likert)	Self-reported rating validated via survey scale	Strong positive
Soft Skills	Problem Solving	Ordinal	Ability to apply reasoning in complex situations	Positive

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Soft Skills	Teamwork	Ordinal	Ability to work in groups effectively	Positive
Soft Skills	Adaptability	Ordinal	Flexibility in changing work conditions	Moderate positive
Soft Skills	Leadership	Ordinal	Capacity to guide peers or lead projects	Positive
Institutional	Placement Cell Support	Ordinal	Engagement with placement training, recruiter exposure	Strong positive
Institutional	Recruiter Engagement	Continuous	Number of recruiters visiting institution	Positive
Networking	LinkedIn/Networking Use	Binary	Use of professional networks for career purposes	Moderate positive
Extracurricular	Participation Level	Ordinal	Involvement in cultural, sports, or voluntary activities	Moderate positive
Demographic	Gender	Binary	Male/Female, included to analyze disparities	Context-specific
Demographic	Socio-economic Status	Ordinal	Family income bracket	Context-specific
Demographic	Location Origin	Binary	Rural/Urban background	Context-specific

Source: Researchers estimation based on literature and inputs from industry experts

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The chart shows evaluation metrics including accuracy and precision and recall and F1-score which enables interpretation through odds ratios and feature attribution. The last part shows how research results produce useful knowledge which helps students and educational institutions.

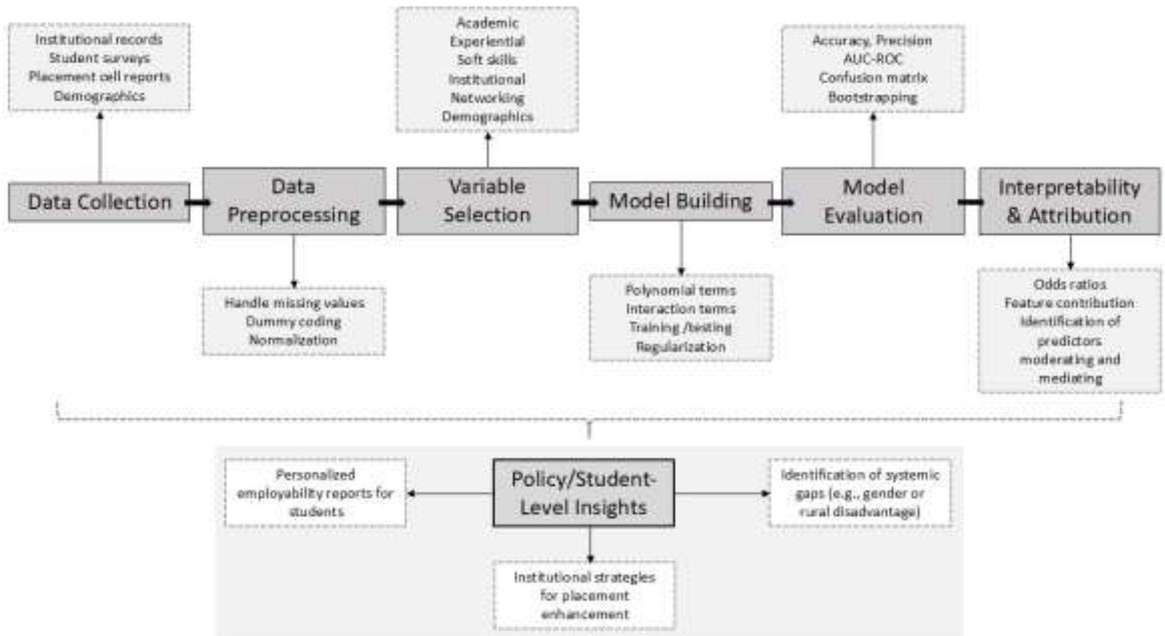

Fig 1: Flow of research

4. Model development

The employment prediction model is constructed using a logistic regression framework, which provides a probabilistic approach to binary classification. The goal of this problem is to predict employment status ($y = 1$) or unemployment ($y = 0$) for N postgraduate students based on their feature vector $X \in \mathbb{R}^{18}$ which contains academic, behavioral, experiential and demographic information.

The first step requires standardization of each feature to establish numerical stability which helps prevent scale bias during model training.

$$Xz = (X - \mu) / \sigma,$$

The model uses the following parameters where $\mu \in \mathbb{R}^{18}$ and $\sigma \in \mathbb{R}^{18}$ represent the vector of feature-wise means and standard deviations calculated from the training data. To capture non-linear relationships and interaction effects that cannot be modeled by simple linear terms, the feature space is extended by constructing a polynomial expansion with interaction terms:

$$X_{poly} = [X_z, X_{z^2}, \left(X_{z_i} \times X_{z_j}\right) for\ 1\ \leq i\ < j\ \leq 18]$$

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The model includes Xz^2 as an element-wise squared term to represent second-order effects and $Xz_i \times Xz_j$ to model the interactions between different features. This transformation increases the dimensionality from 18 to m = 18 + 18 + (18×17)/2 = 171 features. The logistic regression model predicts the probability of employment using the sigmoid (logistic) function:

$$p(y = 1 \mid X_{poly}) = \sigma(\beta_0 + \beta^\intercal X_{poly})$$

where, $\sigma(z) = \frac{1}{1+e^{-z}}$, $\beta_0 \in R$ is the intercept, $\beta = (\beta_1, \beta_2, \ldots\ldots \beta_m)^\intercal$, $X_{poly} = (X_{poly,1}, X_{poly,2}, \ldots \ldots \ldots \ldots X_{poly,m})^\intercal$ is the vector of polynomial features.

The model includes an intercept term β_0 which belongs to the set of real numbers and m coefficients β that were determined during the training process. Model training is formulated as a maximum likelihood estimation (MLE) problem. The likelihood function is defined as:

$$L(\beta) = \prod_{i=1}^{N} p_i^{y_i}(1 - p_i)^{(1-y_i)}$$

Where, N = total number of observations, $y_i \in \{0,1\}$ = observed outcome for observation I, $p_i = P(y_i=1 \mid x_i;\beta)$ = predicted probability of employment for student I and β = vector of model parameters (coefficients). So, the product expansa as:

$$L(\beta) = \left(p_1^{y_1}(1 - p_1)^{1-y_1}\right)\left(p_2^{y_2}(1 - p_2)^{1-y_2}\right) \ldots\ldots (p_N^{y_N}(1 - p_N)^{1-y_N})$$

The parameters β are learned by maximizing the log-likelihood function logistic regression, which is derived through the Bernoulli model. For observation $_i$ with features x_i and outcome $y_i \in \{0,1\}$, assume:

$$y_i \sim Bernoulli\ (p_i),$$

So, the probability mass function is:

$$P(y_i|p_i) = p_i^{y_i}(1 - p_i)^{1-y_i}$$

In logistic regression we model p_i with the logistic (sigmoid) of a linear predictor:

$$p_i = \sigma(x_i{}^\intercal\, \beta) = \frac{1}{1 + e^{-x_i^\intercal \beta}}$$

Assuming observations are independent, the joint likelihood for N observations is the product of the Bernoulli PMFs:

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$$L(\beta) = \prod_{i=1}^{N} P y_i \mid x_i, \beta = \prod_{i=1}^{N} p_i^{y_i} (1 - p_i)^{(1-y_i)}$$

Maximizing a product is numerically awkward, so take logs (monotone transform). The log-likelihood is

$$l(\beta) = \log L(\beta) = \sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

Substituting $p_i = \sigma(x_i^{\intercal} \beta)$ to get the log likelihood as a function of β. A fitting algebraic reorganization will give:

$$l(\beta) = \sum_{i=1}^{N} [y_i (x_i^{\intercal} \beta) - \log(1 + e^{x_i^{\intercal} \beta})]$$

because, $\log p_i = -\log (1 + e^{-\eta_i})$ and $\log(1 - p_i) = -\log (1 + e^{-\eta_i})$ with $\eta_i = x_i$. Both forms are equivalent and often the second is used for cleaner derivatives.

Differentiate ℓ(β) w.r.t. β. Using vector form, let X be the N × p design matrix (rows $x_i^{\intercal}$), y the N × 1 vector of outcomes, and p the N × 1 p_i. The gradient is:

$$\nabla_\beta l(\beta) = \sum_{i=1}^{n} x_i (y_i - p_i) = X^{\intercal} (y - p)$$

Setting this equal to zero gives the normal equations for logistic regression. Differentiate again to get the Hessian. Define a diagonal matrix W with $w_i = p_i(1 - p_i)$, then the Hessian is

$$H(\beta) = \nabla_\beta^2 l(\beta) = -X^{\intercal} W X$$

To find the MLE $\hat{\beta}$ we can use Newton's method. Given current $\beta^{(t)}$, update:

$$\beta^{(t+1)} = \beta^{(t)} - H\left(\beta^{(t)}\right)^{-1} \nabla_\beta l(\beta^{(t)})$$

Plugging gradient and Hessian gives the iterative reweighted least squares (IRLS) form:

$$\beta^{(t+1)} = \beta^{(t)} + (X^{\intercal} W X)^{-1} X^{\intercal} (y - p)$$

which is algebraically equivalent to solving a weighted least squares problem for the "working response"

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$$z = X\beta^{(t)} + W^{-1}(y - p)$$

This is the standard GLM logistic regression fitting algorithm (what functions like `glmfit` do). To improve generalization and avoid overfitting from the large number of polynomial features, regularization techniques such as L2 (Ridge) regularization could be incorporated, although in this implementation, explicit regularization was not applied, relying instead on model validation metrics. The model uses a probability threshold (t) which was determined through empirical optimization during training to achieve the highest possible accuracy instead of using the standard 0.5 threshold.

$$\hat{y} = 1 \text{ if } p \geq t; 0 \text{ otherwise.}$$

The same preprocessing operations of standardization and feature expansion are performed for each new student to generate their employment probability prediction. The model generates both a binary prediction and interpretable coefficients that show the influence direction and magnitude of each base and interaction and squared feature which enables both predictive accuracy and decision-making capabilities. The structured method enables researchers to find complex non-linear patterns and interaction effects in student data which produces superior prediction results than linear models while maintaining model interpretability.

5. Complete Machine Learning Model Programmed in Octave

The following scrip has been developed to be run in Octave using logistic regression for the employment prediction for students.

```
## ===== STEP 1: Preparation and loading of the data  =====

pkg load io;

pkg load statistics;

datafile = 'file name';

fid = fopen(datafile, 'r');

header_line = fgetl(fid);

fclose(fid);

feature_names_all = strsplit(header_line, ',');                    %
cell array of all column names


data = dlmread(datafile, ',', 1, 0);                                %
2040 x 19 numeric
```

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```
X = data(:, 1:end-1);                                                  %
18 features

y = data(:, end);                                                      %
Employment status (0/1)

feature_names = feature_names_all(1:end-1);

mu = mean(X, 1);

sigma = std(X, 0, 1);

sigma(sigma == 0) = 1;                                                 %
avoid divide-by-zero

Xz = (X .- mu) ./ sigma;

printf('Rows: %d  |  Features: %d\n', rows(Xz), columns(Xz));

printf('Example feature order:\n');

disp(feature_names(:)');


## ===== STEP 2: TRAIN LOGISTIC REGRESSION =====

assert(all(ismember(y, [0,1])), 'Target y must be binary 0/1.');

[b, dev] = glmfit(Xz, y, 'binomial', 'link', 'logit');   %
b(1)=intercept, rest=coeffs

z_train = b(1) + Xz * b(2:end);     % linear predictor

p_train = 1 ./ (1 + exp(-z_train)); % sigmoid probabilities

yhat = p_train >= 0.5;


train_accuracy = mean(double(yhat == y));

printf('Training accuracy (threshold=0.5): %.2f%%\n',
100*train_accuracy);

save('employment_glm_model.mat', 'b', 'mu', 'sigma',
'feature_names');

printf('Saved model to employment_glm_model.mat\n');


## ===== STEP 3: Predict for new student =====
```

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```
new_student = [1,2,3,1,1,1,3,2,3,1,2,1,3,1,2,2];
new_z = (new_student - mu) ./ sigma;
z = b(1) + new_z * b(2:end);       % intercept + dot product
p = 1 ./ (1 + exp(-z));            % sigmoid
label = p >= 0.5;
printf('Predicted probability: %.3f -> Class %d\n', p, label);
```

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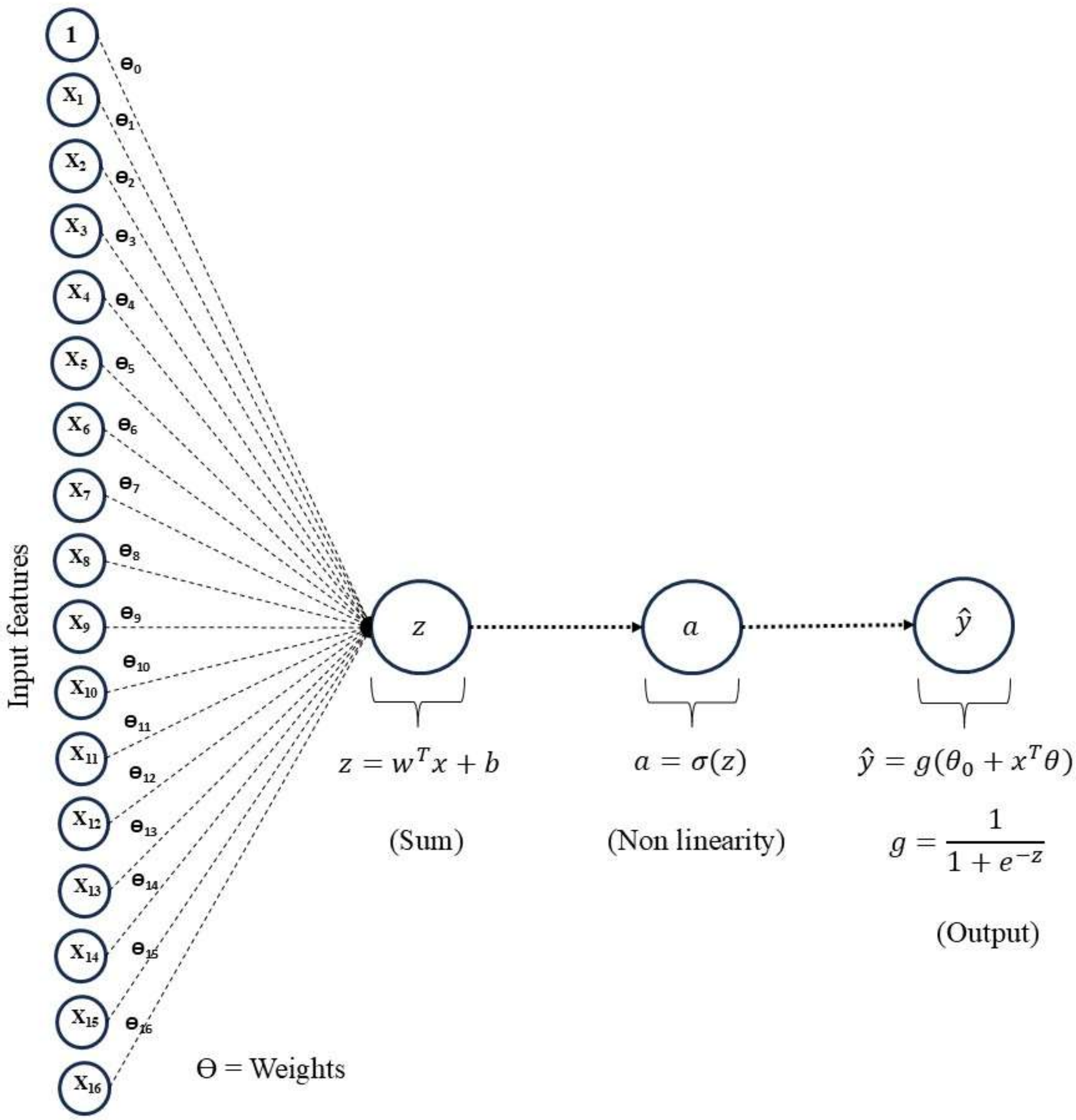
Fig 2: Employment Prediction Framework With No Hidden Layer



Source: Researcher's formulation of the Logistic Regression model.

Figure 2 explains the structure of the employment prediction model using logistic regression. The model takes multiple input features related to a candidate's profile, such as education, skills, and experience. Each input is multiplied by a corresponding weight, and their sum forms a single value

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(z). This value is then passed through a sigmoid function, which transforms it into a probability between 0 and 1. The final output represents the likelihood of the candidate being employed. This simple yet effective model does not use hidden layers, making it easy to interpret while providing accurate predictions for binary outcomes like employed or unemployed.

5.1 Performance metrics of the model

Table 1: Prediction strength of the employment prediction model

Precision	Accuracy	Recall	F1-score
0.920 (92.0%)	0.897 (89.7%)	0.893 (89.3%)	0.906 (90.6%)

Source: Model implementation in Octave

Table 1 reports the prediction strength of the model. With precision and accuracy both being over 80%, this model depicts strong predictive power.

6. Analysis and Discussion

The results of the employability prediction model developed through logistic regression provide meaningful insights into the structural determinants of postgraduate employment outcomes in Jharkhand and, by extension, in similar regions across India. The model analyzes academic and experiential factors together with soft skills and institutional and demographic data to reveal patterns between individual success narratives and educational and economic frameworks. The research produces multiple results which connect student-specific characteristics to both economic development indicators and social welfare metrics and national policy choices.

One of the most significant findings of the model is the central role of experiential learning variables internships and projects in shaping employability. Students who had previous work experience found employment at higher rates than students who did not have work experience. The study confirms that human capital development requires more than theoretical knowledge because it needs practical application in productive settings according to economic principles. The situation demonstrates that India requires better connections between academic institutions and industries to decrease employment market challenges and enhance the standard of new workers entering the economy. The improved employability of graduates enables them to enter the workforce more easily which helps decrease the high rates of unemployment and underemployment that affect India's labor market.

The model showed that communication skills and adaptability and teamwork abilities were the key factors for achieving success. While academic performance such as CGPA remains important, it is insufficient by itself to secure employment. Employers choose the skills which help new graduates succeed in their fast-changing professional settings. The social implications show a cultural shift because modern employability standards demand proof of readiness for work beyond simple memorization and test scores. The method will help educational institutions create curricula that teach employability skills to align Indian higher education with worldwide job market needs.

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The model revealed that institutional support through effective placement cell operations and recruiter participation demonstrated a strong moderating influence. The students who demonstrated academic and soft skills proficiency faced major employment challenges because their educational institutions failed to provide adequate job placement assistance. The research results demonstrate that educational institutions need to work together to improve student employment results. The policy implications indicate that better placement infrastructure combined with recruiter visit incentives will produce significant social benefits. The government supports these institutional mechanisms because they help achieve employment goals through “Skill India” and “Atmanirbhar Bharat” programs.

The research findings showed that participants faced structural discrimination because of their rural or urban origins and their gender expression. Students who lived in rural areas and achieved the same academic results as their urban counterparts faced limited employment opportunities. The gender gap persisted but became less noticeable because women students comprised fewer numbers in fields which experienced high demand. The research findings show that students need particular programs which offer mentorship support and financial help and rural outreach services to establish fair educational opportunities for every student. The achievement of equity requires addressing these gaps because unexploited talent resources create economic inefficiencies which slow down national development.

From the perspective of macroeconomics, employability outcomes are closely tied to GDP growth. Graduate employment results in increased total market demand since their earned income allows them to buy products and services. The higher demand leads to increased production which results in higher GDP levels. Graduate joblessness that extends over time prevents people from reaching their full potential while wasting their acquired abilities which hinders economic development. The model provides institutions and policymakers with predictive data which helps them optimize the national output contribution of educated workers. The alignment of education with employability skills enables India to maximize its demographic dividend which experts consider its most valuable resource.

The quality of employment opportunities in a region establishes the standard of living and happiness levels for its local residents. People who keep their jobs stable achieve financial stability and mental peace which leads to better life satisfaction and happiness. The extended job search of postgraduate students results in increased stress levels and diminished self-confidence which could potentially trigger social disturbances. Higher employment rates in society lead to two main benefits which reduce poverty levels and improve healthcare delivery and educational access for every household member. Research findings demonstrate that improving employability serves as a core social development element which directly affects the standard of living for people in India.

Employability creates effects on consumer behavior as one of its many areas of influence. The consumer market for housing and automobiles and electronics and financial services includes employed graduates who live in urban areas. The expansion of employability creates more potential customers for businesses which motivates them to develop innovative products and services. Unemployed graduates reduce market demand through their inactivity which acts as a

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market slowdown. The relationship between employability and consumer confidence and demand drives economic expansion in India's consumption-based economy.

The results of employability affect the production levels and market performance of producers and firms. The recruitment of industry-ready graduates by companies results in lower training and orientation expenses which produces financial savings and enhanced operational performance. The program enables businesses to compete better in both domestic and global markets. The employability prediction model functions as a tool which helps businesses determine the characteristics of successful graduates thus guiding their recruitment methods and university education programs. The partnership between education and industry provides production systems with adaptable skilled workers who support economic growth in India.

The role of government in this context cannot be overstated. Employment generation is a central policy priority, and predictive models such as the one developed in this research can provide governments with evidence-based tools to design interventions. The identification of rural employability gaps enables the development of regional plans for development and skill-building programs that focus on gender differences. The government welfare programs experience reduced financial strain when graduate employability rates increase because more people become self-sufficient and start paying taxes. The positive feedback loop enables the government to increase its funding for infrastructure development and education and social welfare programs.

Employability creates an impact on international trade and competitiveness. The increasing industry-readiness of Indian graduates leads multinational corporations to invest in India because they can utilize the available skilled workforce. The policy enables foreign direct investment (FDI) entry while developing export-oriented sectors to boost India's position in global value chain operations. A prolonged employment gap would stop investments from flowing and prevent India from competing with China because it has successfully linked educational programs to industrial needs. The research results from the model produce effects which extend beyond household work to influence India's position in global economic markets.

The employment results from the labor market influence both the total market demand and supply levels. The demand for goods and services grows when employment rates increase because people gain more purchasing power to buy products and services. The supply side benefits from industry-ready graduates because they increase production capabilities which help businesses meet growing demand without creating price inflation. The fundamental basis for sustainable development exists in the market equilibrium between demand and supply levels. The economy will experience stagnation in aggregate demand because of low employment rates and underused supply capacity which leads to inefficient operations and reduced economic expansion.

The foreign exchange market and balance of payments are similarly affected.The combination of employable graduates who possess industry-specific skills leads to lower domestic joblessness and stronger opportunities for Indian skilled workforce export. This generates remittances, a critical component of India’s foreign exchange reserves.The absence of employment opportunities in India will force educated workers to migrate abroad because they cannot discover appropriate

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employment within their home nation thus resulting in the loss of essential human capital. The improvement of employability leads to better service export performance because India maintains its competitive edge in IT consulting and financial services. The current account receives additional support which leads to better balance of payments results.

The model produces major social consequences. The results of employment lead to social progress which helps reduce social inequalities and generates new possibilities for everyone. The improved employability of marginalized groups enables them to escape poverty as their numbers in professional environments continue to increase. Higher employment rates at the community level create positive outcomes that include better overall community health and reduced criminal activity and increased community involvement. The model demonstrates that soft skills and institutional backing and academic success have equal importance to traditional merit-based systems which create an inclusive educational framework.

The model establishes a philosophical link between employability and the search for happiness and human fulfillment. People who have secure employment receive financial stability while gaining a feeling of life direction and social connection. The prolonged unemployment of educated people in their communities leads to social unrest throughout the community. The research provides predictive data about employability which helps create a society that generates financial returns and mental satisfaction from educational investments.

The research on the employability prediction model shows that postgraduate employability functions as a vital economic and social development factor which extends beyond traditional educational results. The model shows how experiential learning and soft skills matter but it also shows the existing structural barriers that need to be fixed. The economic effects of the pandemic reach multiple areas including GDP expansion and standard of living and market participant interactions and public sector choices and worldwide commerce and total market activity and currency exchange rates and international financial transactions. The research shows that improving employability stands as a vital factor to achieve India's demographic dividend and boost its global market position and deliver better life quality to its people. Predictive analytics integration into policy and practice has turned employability from a long-standing problem into a fundamental force which drives sustainable development for all people.

6.1 Model Interpretation

The logistic regression model shows which variables affect postgraduate student employability results. The logistic regression framework produces coefficients (β) that establish direct relationships between features which enable users to assess both the individual and collective effects of features on the outcome. For each student, the contribution of each base feature to the predicted probability of employment is calculated as:

$$\text{Contribution}_{\text{base}_i} = \beta_i \times Xz_i,$$

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The model uses β_i to represent the learned coefficient which corresponds to the standardized feature Xz_i. The sign of the contribution shows whether a feature makes someone more likely to get a job (positive) or less likely (negative). The absolute magnitude of the contribution reflects the relative strength of the feature's influence. Similarly, the mediation (non-linear) effects are interpreted via squared terms:

$$\text{Contribution}_{\text{Medi}_i} = \beta_{\{\text{squared}_i\}} \times (Xz_i)^2,$$

The β_{squared$_i$} coefficient shows the relationship between the squared values of features and job opportunities. The positive values in the table show that stronger skills lead to exponential growth in employability but negative values indicate that too much of a feature can lead to diminishing or negative returns.

The model includes direct representations of how each feature affects the outcome as well as how different pairs of features interact with each other.

$$\text{Contribution}_{\text{Oder}\{i,j\}} = \beta_{\{\text{interaction\_}\{i,j\}\}} \times (Xz_i \times Xz_j),$$

The model includes $\beta_{\{\text{interaction}\{i,j\}\}}$ as a coefficient which shows the total effect of two specific features on employment probability. Students who demonstrate both technical skills and internship experience achieve higher employability than their individual skills would suggest according to the positive effect of their combined attributes. The system produces automatic summaries for each student through a ranking process that determines the order of influence for base effects and mediation and moderation effects. The most important factors for job acquisition are the top 2–3 positive contributors while the top 2–3 negative contributors show the main weaknesses that affect employability. The interpretive mechanisms function to generate practical recommendations. The large positive contribution of "Communication Skills" indicates that students need to improve their communication abilities further. The current systemic inequalities need policy solutions to address them according to the negative effects of "Demographic Factor".

The model produces an employment prediction together with an extensive evaluation of specific elements which determine job readiness. The analysis enables policymakers and educators and students to determine essential factors which leads to effective development of targeted interventions and skill development programs. The method helps decrease employment uncertainty because it shows particular quantifiable characteristics that enhance job readiness for Indian job seekers.

6.2 Impact of the Model on Reducing Employment Uncertainty

The employability prediction model delivers its main value through its ability to decrease job uncertainty for students who have completed their postgraduate studies. The labor market uncertainty emerges because students along with institutions and employers struggle to understand which factors determine employability and how important each factor is. The lack of clear information about the job market results in inefficient processes which produce unaligned

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expectations and extended employment searches and unnecessary expenditure of human capital and financial resources.

The logistic regression model created in this research handles uncertainty through probabilistic predictions of employability based on student characteristics. Students now obtain individualized job market assessments through this system which moves beyond using personal stories and basic job market statistics. Students discover through this assessment that their academic success does not guarantee employment readiness because they need to improve their communication abilities and gain work experience. The analysis provides clear results which enable students to concentrate their work on their weak points to enhance their job market readiness. The model enables institutions to decrease uncertainty because it reveals which variables generate the most significant impact on employment outcomes. Universities and colleges often struggle to design employability enhancement programs due to unclear evidence of what works. The model enables institutions to create evidence-based intervention strategies through its quantitative assessment of experiential learning and soft skills and placement support. The data shows that recruiter engagement has a significant impact on employment results so placement cells should focus on developing better connections with industries.

The method helps employers to reduce their uncertainty levels. Organizations make multiple hiring attempts because they spend large amounts of money on candidate recruitment and development until they discover that new employees lack essential competencies. The model connects academic skills to demonstrated work value to establish direct links between college learning and employer requirements thus filling the educational skills gap. The system enables organizations to find suitable candidates quickly while reducing the risks that come with graduate recruitment methods.

The reduction of employment uncertainty at the societal level results in improved labor market efficiency and better human capital utilization. Students who receive proper skill development guidance along with specialized institutional programs experience an easier transition from school to work. Through the program more job seekers can join the workforce which leads to better economic results because it decreases the number of unemployed college graduates. The model reveals employment routes to students and institutions and policymakers through its illumination of these paths which converts unknown variables into practical information.

6.3 Policy Recommendations

The research model serves as a foundation for these policy recommendations which focus on improving employability and reducing labor market risks to maximize socio-economic advantages from postgraduate education in India.

Strengthening Experiential Learning

The University Grants Commission (UGC) and other government bodies and educational regulators need to establish mandatory requirements for postgraduate students to complete internships and industry projects and apprenticeships. Students can obtain practical experience

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through structured real-world programs before graduation because of the partnership between local industry and startups and government enterprises.

Soft Skills and Communication Training

The fundamental structure of postgraduate programs should include soft skills education as a core component instead of adding it as an extra feature. The training program requires all employees to complete modules about communication and adaptability and leadership and teamwork which will be assessed through classroom work and practical simulations. The budget of state governments should be used to establish skill labs and employability workshops at universities situated in rural and disadvantaged areas.

Placement Infrastructure Development

The government needs to create professional placement cells which should receive appropriate incentives to actively collaborate with industries. The government needs to create tax incentives and subsidy programs that encourage recruiters to hire students from regional universities in order to boost their presence in non-urban areas. The state needs to establish digital platforms which unite educational organizations with employers to improve their connection and reduce existing knowledge differences between them.

Bridging Rural–Urban Disparities

The system needs to create special programs which will help rural students because they encounter institutional barriers that affect their academic performance equally to their urban peers. The combination of internship scholarships with mentorship programs and industry-specific employability bootcamps creates opportunities for students to achieve equal opportunities in the job market. The labor market transition needs established policies to stop rural graduates from missing out on available job openings.

Employability programs need gender inclusivity to be their core foundation.

The model shows that employability interventions need to focus on the gender differences which exist in the labor market. Organizations should create career support systems that concentrate on women through leadership development initiatives and flexible internship opportunities. Workplace inclusivity needs to be supported through national policies which will drive up employment opportunities for female graduates across multiple industries.

Data-Driven Decision-Making in Higher Education

The predictive model created in this study shows how data analytics can decrease levels of uncertainty. The government needs to back universities in their efforts to establish predictive analytics systems which track ongoing employability results. A centralized employability

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dashboard operating at the state or national level would combine data to support policy decisions while showing employment gaps between areas and enabling ongoing performance monitoring.

Enhancing Global Employability

Given India's increasing role in the global labor market, postgraduate education must also focus on preparing students for international employability. The government needs to establish policies which will motivate educational organizations to offer worldwide recognized certifications and training for foreign language education and cross-cultural programs. The program lets students acquire international work experience which results in improved career prospects and higher remittances that enhance India's position in the worldwide economy.

Higher education institutions need to create strategic objectives which will help achieve national development targets.

Employability needs to become a core component of the entire economic development policy framework. The Ministries of Education Skill Development and Labor need to work together to ensure postgraduate education supports national goals including Make in India Digital India and Atmanirbhar Bharat. The predictive model developed in this research needs to integrate into institutional systems for monitoring the alignment between graduate attributes and present-day industrial and economic needs.

Conclusion

The study examines the expanding Indian higher education sector while identifying its inability to prepare postgraduate students for employment. The research develops a predictive model using logistic regression which combines academic and experiential factors with soft skills and institutional and demographic elements to create a complete framework for employability problem resolution. The model uses statistical methods to predict employment results and determines which factors have the greatest impact thus providing clarity to students and institutions and employers and policymakers.

The research shows that employability consists of various related components. Academic performance through CGPA matters but the combination of experiential learning activities and soft skills development and institutional support systems proves more effective for securing employment. The population distribution between urban and rural areas and the existing gender inequality in the population continue to be essential issues that need attention. The research data shows that organizations must establish a complete organization-wide system to boost employability instead of using individual solutions.

The research findings produce major economic and social effects. The results of employability directly affect both total market demand and national productivity levels and GDP expansion rates and social health indicators. Higher graduate employability creates better consumer confidence which leads to higher labor force participation and improved living standards and generates

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additional government revenue and strengthens international trade performance and balance of payments stability. Secure employment at the societal level creates poverty reduction and happiness improvement and social inclusion through its ability to provide social mobility pathways.

The research creates an operational predictive model which serves as an efficient instrument to direct specific interventions within higher education institutions. Educational institutions use evidence-based decision making through these models while governments create policies by analyzing data which produces tailored feedback for students. India will achieve its demographic dividend potential and develop an education system that links learning to employment by following this approach.

Limitations

The research provides important findings but it contains certain restrictions. The model's predictive accuracy could be limited by its dependence on logistic regression because this method provides interpretable results but may not match the performance of more complex algorithms including random forests and neural networks. Future research could incorporate these methods while balancing interpretability with predictive power.

Second, some of the variables, particularly soft skills, were measured through self-reported surveys.The results of self-assessment may include social desirability bias and overestimation which can reduce the reliability of the results even when reliability checks are performed. Future research should validate its results by using employer feedback and standardized skill assessment methods. The dataset contains information about postgraduate students who live in Jharkhand. The research findings provide useful data but researchers must handle these results with care when they want to use them for other states or nationwide applications. The Indian higher education system and labor market operates with diverse characteristics which demand separate investigations in various fields to generate generalizable findings.

The binary operationalization of employability (employed/unemployed) reduces the complexity of actual labor market results to two categories. The study failed to include employment quality and job satisfaction and income levels and educational background alignment as equally significant factors. Future research needs to create an employability index that assesses various elements which represent these intricate factors. The research took place at a time when labor markets underwent fast transformations because of artificial intelligence and globalization and policy reforms. The dynamic nature of employability means that models require constant updating and recalibration to remain relevant.

The research establishes a solid base to study and enhance postgraduate employment readiness in India although it has certain restrictions. Future research must focus on the identified gaps to enhance predictive models which will help educational planning and labor market efficiency and sustainable economic development.

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References

Almeida, F., & Simoes, J. (2020). The role of higher education institutions in promoting employability skills in the digital age. *Education and Information Technologies, 25*(4), 1–15. https://doi.org/10.1007/s10639-020-10148-6

Bajpai, N., & Verma, S. (2021). Employability challenges of Indian graduates: Role of curriculum and industry interface. *Higher Education for the Future, 8*(1), 24–40. https://doi.org/10.1177/2347631120970691

Choudhury, P., & Singh, R. (2021). Enhancing employability in Indian higher education: Policy initiatives and outcomes. *Journal of Education and Work, 34*(3), 317–332. https://doi.org/10.1080/13639080.2021.1901722

Government of India. (2020). *National Education Policy 2020*. Ministry of Education. https://www.education.gov.in/sites/upload_files/mhrd/files/NEP_Final_English_0.pdf

Gupta, A., & Sharma, R. (2022). Skill mismatch and unemployment in India: A labor market perspective. *Indian Journal of Labour Economics, 65*(2), 453–472. https://doi.org/10.1007/s41027-022-00387-8

International Labour Organization. (2021). *World employment and social outlook: Trends 2021*. ILO. https://www.ilo.org/global/research/global-reports/weso/2021

Khan, T., & Mishra, P. (2022). Impact of internships and experiential learning on employability of postgraduate students in India. *International Journal of Educational Development, 92*, 102600. https://doi.org/10.1016/j.ijedudev.2022.102600

Kumar, S., & Narayan, A. (2021). The future of work in India: Implications for employability and higher education. *Asian Journal of Management, 12*(4), 543–550. https://doi.org/10.5958/2321-5763.2021.00102.9

Mitra, S., & Banerjee, R. (2021). Graduate employability and skill gap: Evidence from Indian higher education. *Higher Education Policy, 34*(3), 553–574. https://doi.org/10.1057/s41307-021-00230-6

NITI Aayog. (2021). *Strategy for New India @ 75*. Government of India. https://www.niti.gov.in

Patel, D., & Mehta, K. (2023). The role of soft skills in enhancing employability: Evidence from Indian management graduates. *Journal of Education and Training Studies, 11*(2), 67–78. https://doi.org/10.11114/jets.v11i2.6124

10.48047/jocaaa.2024.33.07.55
EISSN:1572-9206
ISSN:1521-1398

Reddy, V., & Anitha, P. (2020). Employability skills of engineering graduates: A gap between industry expectations and academic outcomes. *Journal of Engineering Education Transformations, 34*(1), 50–56. https://doi.org/10.16920/jeet%2F2020%2Fv34i1%2F149628

Reserve Bank of India. (2022). *Report on currency and finance 2021-22: Revive and reconstruct*. RBI. https://rbi.org.in

Sharma, M., & Dey, S. (2021). Employability in the post-COVID era: A case for hybrid skills. *Journal of Education and Work, 34*(7), 891–908. https://doi.org/10.1080/13639080.2021.2005583

Singh, A., & Ghosh, S. (2023). Predictive analytics in employability: Machine learning applications in Indian higher education. *Computers and Education: Artificial Intelligence, 4*, 100113. https://doi.org/10.1016/j.caeai.2023.100113

World Bank. (2020). *World development report 2020: Trading for development in the age of global value chains*. World Bank. https://www.worldbank.org

World Bank. (2022). *India development update: Navigating the storm*. World Bank. https://www.worldbank.org