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AN IN-DEPTH STUDY ON THE DEVELOPMENT AND COMPETITIVE ANALYSIS OF THE JOB PORTAL INDUSTRY

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ABSTRACT: Economists and social scientists can use big data analytics to complement traditional information sources and solve economic challenges. Data generated by today's online systems tends to be rich in variety, detail, and dimensions. Shine Jobs, an Indian job site, demonstrates how data from online job portals may be utilized for labor economics and workforce skills development research that is important to policy. Data from online job portals has the potential to enhance labor market policies and analytical abilities in five primary areas: monitoring and analyzing the labor market; assessing the demand for skills in the workforce; matching the skills of job seekers with available positions; predicting the need for skills; and conducting experimental studies. Descriptive, time-series, text, predictive, and transactional analyses are all possible using the data collected through online job-search portals.

Key words: labor market analytics, big data, wage, gender, skills demand, behavioral, forecasting

1. INTRODUCTION

Education and skill-building enhance worker productivity, poverty, and economic progress. Thus, many nations emphasize education to boost human capital and economy. "Skills have become the global currency of the 21st century" (OECD, 2012). Recent research (Hanushek and Woessmann 2008, 2011) show that economic growth depends more on education and skill training quality than quantity. This new evidence and significant progress in expanding and improving primary education have shifted human capital formation in international development discourse from universal primary education under the UN Millennium Development Goals to skills development and job creation under the SDGs. SDGs foster employment, entrepreneurship, and high-quality, employer-relevant skills training. The World Bank recognizes lifelong human capital formation (World Bank, 2010). Technology and internet connectivity have produced new, multi-skilled occupations. In today's digitalized global economy, machines drive and write. Future policymakers should prioritize non-automatable talents (World Bank, 2016). Critical thinking, complex problem-solving, and rationality are examples. These skills earn 25-40% more than traditional workers with comparable education (World Bank, 2016).

Human capital development and mismatches between employee capabilities and employer demand limit economic growth. Skills mismatches, whether major or minor, are problematic. Labor market-education-training disconnects cause macro-skills mismatches. Many countries lack precise real-time employment data and demand-driven skills-development systems. Due to labor market information and coordination issues, companies may struggle to find qualified personnel. Few institutions have complete data on local talent shortages and demand. Informal labor market supply and demand analyses are rare in emerging economies despite their magnitude and economic importance. Thus, job-talent matching and keeping training providers informed of labor market demand changes are crucial.

Online job-search engines and other employment services are helping address labor market information asymmetry and coordination challenges. LinkedIn, Indeed, Monster, and CareerBuilder connect businesses and job seekers globally. Local online employment portals provide official and informal sector opportunities for internet users in areas where such websites are scarce. Policymakers use global and regional web platforms' labor market data slowly. Labor economists are increasingly analyzing huge data from internet job marketplaces. Despite its representativeness difficulties, Kureková et al. (2022) found online job-portal data useful for their literature review. Labor economics uses workforce and home sample surveys. Rare polls have large coverage gaps. Big data may expose ancient economic challenges, speed economic research, and improve public policy with multidimensional, detailed, real-time information.

Objectives

Shine jobs, an Indian online job-matching platform, is used to explore how online job-portal data affects academic research and policymaking. This research seeks to improve labor market policies in India and worldwide. Economics big data analytics has focused on theoretical foundations and data-source analysis rather than actual implementations. This article uses Shine employment data to evaluate big data analytics research applications. Indian data is rare in impoverished country case studies. Internet employment sites in India update data less often than in the US and Europe, making labor market trends difficult to track. This study can illuminate the Indian labor market and show how big data analytics can improve labor market policy and demand-driven skill development.

2. LITERATURE REVIEW

In the early 2000s, advances in data processing, broad internet adoption, and strict data gathering produced an unprecedented wealth of precise, real-time information about human and institutional behavior, coined "big data." Big data has all three (Laney, 2001). Big data analytics first helped organizations adapt to client habits. Since then, big data analytics has connected theory and practice, according to Savage and Burrows (2007, 2009; Taylor, Schroeder, and Meyer (2020). Economics and social sciences quickly adopted big data. Big data can improve research methodologies and economic tracking. These data may assist economists understand economic activity and demographic variation. Big data's real-time, scale, multidimensionality, granularity, and recording capabilities improve economics, according to Einav and Levin (2013).

Big data helps researchers access job market data (Horton and Tambe, 2022). Marinescu and Rathelot (2022) used "Career Builder," an online US employment marketplace, to study how location impacts job-seeker behavior. Although job seekers may move for the perfect chance, frictional unemployment in the labor market is not caused by distance. Big data analysis was needed. US, European, and middle-income countries like China and Slovakia use employment portal data. LinkedIn, Facebook, Twitter, Glassdoor, and Google Trends can reveal employment market trends (Lenaerts, Bevlavy, & Fabo, 2016). Online employment markets allow job-seekers and companies to acquire data cheaply. Kroft and Pope (2021) and Mang (2012) conclude that the general shift from print to internet job advertising has reduced labor market data costs. Employment websites reduced unemployment in developed countries, however Shahiri and Osman (2021) found no significant effect on earnings. According to Shahiri and Osman (2021), many people in underdeveloped nations cannot use employment websites due to poor internet infrastructure, high user fees, or a lack of IT skills. Information restrictions are a major, but often overlooked, source of labor market inefficiency (Klonner and Nolen, 2010 for South Africa; Aker, 2011 for Niger; Burga and Barreto, 2021 for Peru), and cellphone use improves employment outcomes in

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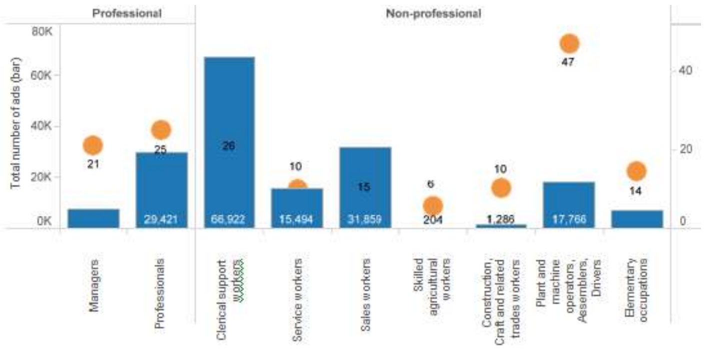
developing countries. Big-data labor market analysis is difficult. Privacy, security, creative classification and analysis of vast unstructured data sets, and scalability are vital. Data ownership and methodology matter. Big data analytics ignores the micro-processes that create big data's network properties (Snijders, Matzat, and Reips, 2012).

3. THE INDIAN LABOR MARKET, SKILLS DEVELOPMENT AND SHINE JOBS

India's economy has grown and poverty has decreased. India's GDP rose 7.3% from 2007 to 2012. This ended poverty for 138 million. India fails to boost worker productivity and match labor market skills despite strong growth. Big, casual, young Indian labor. 2021 employed 497 million Indians.3 4.2 million people joined the workforce in 10 years. 26% of workers are women, 80% men. Only 16% (18% men, 12% women) are wage-employed. 54% under 25. Youth need fulfilling government work. Many Indian youngsters are untrained. Employment and skill development are crucial. The 2022 National Policy for Skill Development and Entrepreneurship and 12th Five-Year Plan aim to train 400 million workers to overcome these issues. National Sample Surveys collect India's labor market data. Annual Survey of Industries and quarterly employment surveys by the Central Statistical Organization track industry and labor development in certain economic sectors. IFC 2021). The Indian government typically samples families and industry to determine labor market trends and skills requirement.

Online job portals began in India in the late 1990s, but mobile phone and internet use and social media platforms have grown them. Mobile customers tripled from 20% in 2007 to 70% in 2021, and fixed broadband eightfolded. About 20 job search platforms, many Indian-focused, exist.4 Shine Jobs began in 2007. Between 2007 and 2022, the site has 858,000 jobs, 240,000 employers, and 4.5 million job seekers. Shine Jobs uniquely matches people to formal and informal companies. Shine Jobs addresses poor people through websites, mobile sites, IVR, texting, and web apps. 5 Entry-level clerical support advertising dominated Shine positions in 2022.India's 10 major cities—Bangalore, Delhi, Mumbai, Chennai, Hyderabad, Pune, Kolkata, Thane, Patna, and Lucknow—accounted for 70% of advertised openings. Professionals earned 17% more (Rs. 14,900) than non-professionals (Rs. 12,739). Professional salaries ranged from 16,970 in Mumbai to 12,757 in Patna (33%), while non-professional salaries ranged from 14,184 in Delhi to 10,742 in Patna (32%).

Figure 1: Shine Job Listings by Occupational Category, 2022



4. ANALYZE LABOR MARKET DYNAMICS IN INDIA: THE CASE OF SHINE JOBS

Labor Market Monitoring and Analysis

Real-time job-portal data tracks labor market trends. Government and sample-based labor force and company surveys can incorporate big data employment data. Demographics, earnings, experience, employer size, and staff makeup are collected in labor force surveys. Formal business and production surveys assess worker productivity. Workforce and enterprise surveys rarely address several factors. Real-time job-portal data aids analysts and policymakers. Online job portals offer real-time monitoring, data granularity, and originality above survey tools. Online job adverts can show labor market demand

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by time, area, and occupation. Only salary offers on online job portals can demonstrate skill demand, hiring seasonality, and employers' production predictions for specific professions. Official statistics track wages and distribution. Data segment labor markets. Policymakers study job opening growth, dispersion, wage trends, and job seeker competition. Limited job-portal data. Well-defined, publicly available labor market data is needed for appropriate interpretation. Statistically weighting data by labor force survey industry structure, focusing on labor market segments with reduced coverage bias, and employing multiple data sources to parallel evaluate and corroborate findings can address representativeness difficulties (Kureková, Beblavý, and Thum-Thysen, 2022).

Application of the Analysis to Shine jobs Data

Online job-portal data can examine social groups and labor market categories. This Shine employment data analysis analyzed gender compensation differences for similar positions. 26 percent of Indian workers are women, and gender inequalities in employment are a development issue (UN, 2012). Between 2007 and 2022, 240,000 employers filed 858,000 Shine positions with wage offers. An econometric study found that occupations requiring a male hire had 7.1 percent higher average wage offers than those open to both genders, while those requiring a female hire had 16.2 percent lower offers. Work period, location, occupation, and contract type affected salaries in this investigation. Cooks, garment, and teaching jobs had higher income differentials than stewards, nannies, machinists, and office assistance (Figure 2). Ahmedabad, Ranchi, and Thane had the largest gender wage gaps among the 20 cities with the most job listings (Figure 3). Indore, Noida, and Gurgaon were closer.

Figure 2: Gender Wage Gap by Occupation

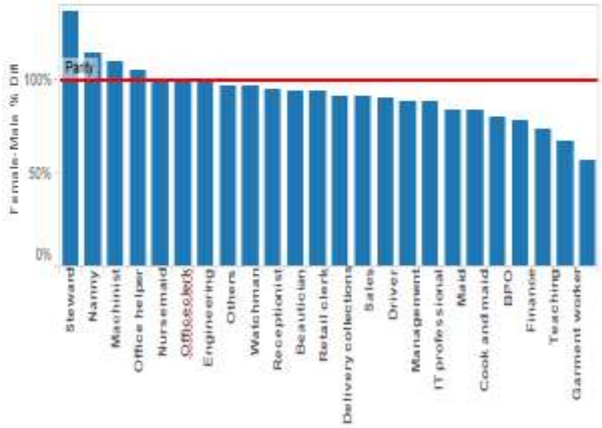
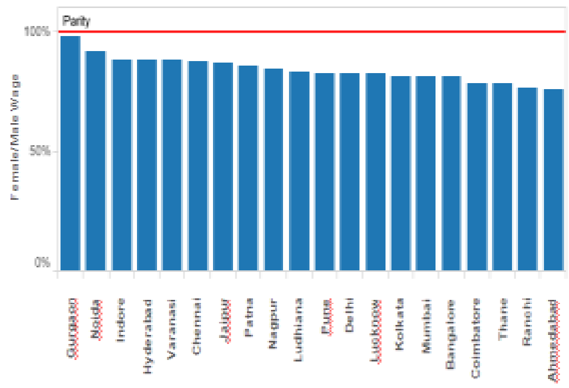


Figure 3: Gender Wage Gap by Location



Many nations have gender wage gaps. India's low female workforce participation rate makes wage difference crucial. Location and occupation gender differences were significant. Lower income differentials in Gurgaon, Lucknow, and Noida may encourage women to work. Professional women may not have lower salary disparities. Equal pay may help women work, but more research is needed.

Assessing Demand for Workforce Skills

Skills demand drives workforce policy. Unemployed or underemployed educated and competent workers may not be needed. Some educational institutions partner with specific organizations to ensure their graduates have the skills employers want, although present and future workers may not know labor market demand patterns. Most employer-demand surveys are subjective. Cunningham and Villasenor (2016) examined 27 foreign employer skills studies. Employers emphasized socio-emotional and high-order cognitive skills over technical and basic cognitive skills. Employer surveys can focus

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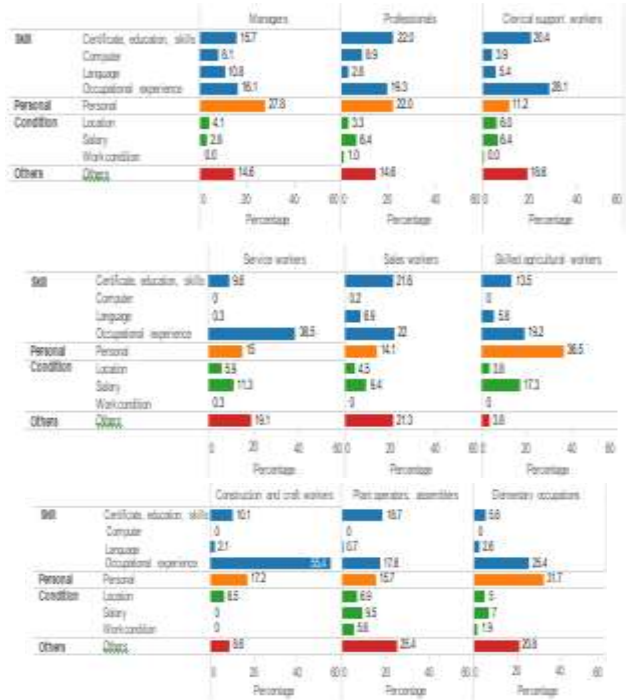
education and skills training, but their subjective and qualitative nature makes it challenging to compare talents and skill combinations (Rutkowski, 2010).

Big job portal text analysis quantifies employer demand. Text analysis categorizes huge textual material. Examine keyword frequency, content, and structure. Text analysis helps labor market analysis. Polls may underestimate employers' skills. Website job ads don't cost per word, so companies can list more talents and knowledge (Gallivan et al. 2004). These descriptions may demonstrate what skills and pay different jobs require. Sample-based labor force surveys cannot collect this data. Beblavý, Fabo, and Lenaerts (2016a) evaluated two million US Burning Glass employment ads. Education, formal qualifications, cognitive talents, non-cognitive skills, and experience were grouped and subcategorized. Based on employee ability, employment ads emphasised cognitive and non-cognitive skills. 25% of job ads mentioned computer abilities, but just 9%, 21%, and 39% for low-, medium-, and high-skilled individuals. 21 percent, 47%, and 45% of job ads for low-, medium-, and high-skilled workers required non-cognitive service skills. Beblavý, Fabo, and Lenaerts (2016b) examined foreign language demand in Czech, Hungarian, Polish, and Slovak employment adverts. 28 percent of Czech Republic posts and 64 percent of Polish posts required foreign-language skills. 52% needed English.

Application of the Analysis to Shine jobs Data

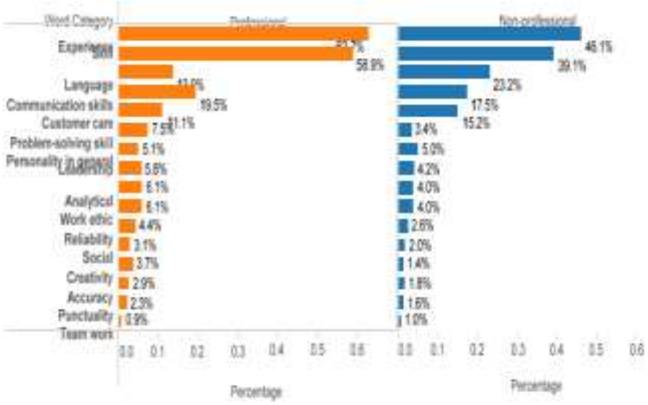
Shine employment data determined employer capabilities in two ways. Assess employer qualification screening questions. Second, use job description text analysis to determine skill need. Figure 4 shows occupation-specific screening questions. Skills, personality, employment, and benefits were screened. Language, computer, and professional experience. Location, compensation, and bonuses are job conditions. Other inquiries are job-specific. Skills-based screening filters predominate. Management (50.7%) and professional (47.9%) credentials checks include skills questions. Clerical, service, construction, and craft workers prioritize experience over education and technical skills. Salespeople and managers need English and Hindi. Personal information queries are frequent for maids, chefs, and gardeners since employers value basic information. Gender, age, police verification, résumé, and photographs are needed. Acceptance of job terms—including compensation and hours—also influences hiring decisions.

Figure 4: Common Screening Questions by Occupation



Text analysis shows employer preferences for cognitive and non-cognitive skills. Employers rarely request non-cognitive skills. Job advertisement analysis may be more accurate than employer interviews and surveys since it reflects organizations' real-world activity. FIGURE 5. Highlight qualifications in job descriptions. (Figure 6). Professions emphasize skills. Professionals and non-professionals use "experience" and "communication" most. "English" and "customer/client" are informal. Non-professional ads emphasize language and customer service, while professional ads highlight problem-solving, leadership, analytical skills, work ethic, reliability, creativity, and personality. Professionals need higher-order cognitive and non-cognitive skills. Job adverts neglect non-cognitive capabilities. Contrary to India (Blom and Saeki, 2011) and elsewhere (Cunningham and Villasenor, 2016), employers emphasized non-cognitive skills. Interviews may be used to assess subjective non-cognitive skills. Despite testing challenges, job ads should highlight non-cognitive skills.

Figure 5: 2021 Job Ads with Keyword Clusters by Occupational Level



Text analysis yields more employer-desired employee traits than questionnaires. Job searchers may benefit by linking basic cognitive, non-cognitive, and technical skills to specific jobs. Text analysis may extend to shortlisted job applicants' CVs. These evaluations help policymakers and educators prioritize skills training.

Observing Job-Search Behavior and Improving Skills Matching

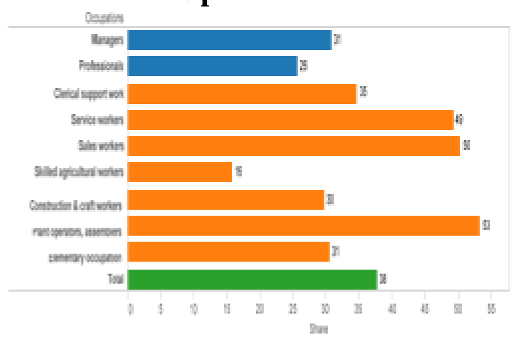
International development professionals investigate psychological, social, and cultural elements that affect economic decisions using behavioral economics (World Bank, 2022). Development economists need behavioral data on personality traits and psychological features, yet surveys, questionnaires, and other common approaches employ self-reporting. Hiring and job-seeking are tracked online. Urgency, field availability, income, and location must be considered. Job-seeking behavior isn't captured by sample surveys. Online job-portal behavioral analysis is unique, but applying it to non-experimental data should reduce worker skill supply-demand friction. Policymakers could reduce skills mismatches by understanding job candidates' incentives using behavioral economics. Indian policy might be influenced by employment classifications and application timing.

Application of the Analysis to Shine jobs Data

Personal circumstances and employer demand effect job searchers. Chronic unemployment or financial hardship may require distinct coping techniques (Lazarus 1991; Lazarus and Folkman 1984; Liu, Huang and Wang 2021). Education allows low-skilled work. Less-educated persons have fewer job possibilities.

Figure 6 Professional group shine treatments. Managers and professionals sought more work. 31% of management candidates and 26% of professionals sought one position. Flexible professionals. Non-professionals applied. 50% of service, sales, factory, and assemblers applied for one job. These groups may use a talent or expertise. Drivers and beauticians picked one career. Skilled agricultural, elementary, building, and craft workers sought more work. Less skilled workers may be more sensitive to remuneration, employment terms, and other non-job matters. Clerical-support applicants were flexible.

Figure 6: Worker Applications by Main Occupation Choice



Job posting-application correlations were examined. Using Shine employment data and time-series analysis, Yamauchi et al. (forthcoming) examined workforce skill demand and supply. Job applications and advertising show

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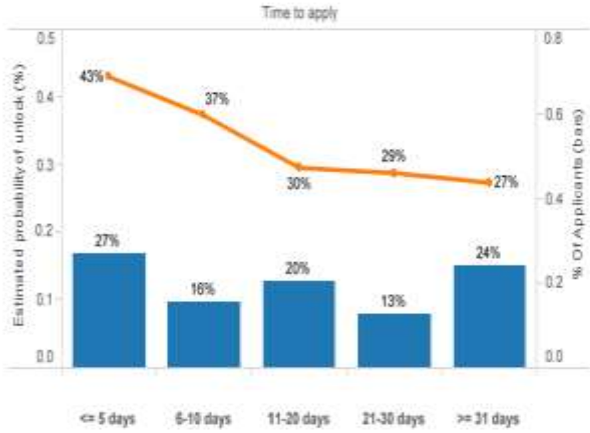
high margins. Between 2012 and 2022, business-process outsourcing (BPO) jobs advertised daily in Bangalore were quickly filled, suggesting that the quantity of required skills was not a binding constraint and that the quantitative skills gap between demand and supply for BPO jobs in Bangalore appears to be relatively small. After job ads increased, most applied within two days. BPO jobs are posted quickly by Shine Employment. Job search success implies responding. Assessed employer hiring schedules. Top talent is scarce, yet employers want them. Simon 1955; Iyengar, Wells, and Schwartz 2006 state that companies must find the best candidate at the lowest cost. 8 (Figure). 27% of the 173,044 applications for the 919 BPO jobs granted between January and October 2022 in the 10 locations as part of the shortlisting service package were submitted within 5 days, 16% between 6–10 days, and 76% within one month. Selecting 29.9%. Applying early is statistically significant, according to probability model econometrics. 120-720 hours. Applying within 5 days was 15.6% more likely to be shortlisted than applying after 30 days, controlling for location, number of jobs, month, and basic candidate qualities. This advantage declines to 9.9, 2.2, and 1.4 percentage points for 10-, 20-, and 30-day applications. Companies prefer applications submitted within 10 days of a job posting to fill vacancies quickly. Quickly applying boosts chances of being shortlisted. Future studies may compare the costs of swiftly filling a position vs finding a quality candidate.

Figure 7: BPO Job Shortlist Probability by Application Submission Time



Predictive Analysis of Skills Demand

Labor market trends and history predict online job-portal statistics. Labor market skills mismatches prohibit many developing countries' workforce training institutes from enhancing graduates' job prospects. Due to poor labor market data, analysts and policymakers estimate skills demand to focus training programs. Policymakers may wait years for workforce survey data. "Manpower planning" estimates government labor demand. Headcount imbalances and subjective employer surveys define occupation staffing needs in manpower planning. Policymakers use other labor market studies due to its limitations (Psacharopoulos 1991). CEDEFOP 2010 and ILO 2016 track regional employment. Econometric modeling includes macroeconomic, demographic, data constraints, and missing non-survey data (ILO 2010). Occupation, training type, and educational attainment labor market predictions are unusual due to data paucity and difficulty integrating data into economic projections (Maier, Monnig and Zika 2022). Online "nowcasting" and forecasting measure labor market changes and skills needs without the subjectivity and latency of workforce surveys. Askitas and Zimmermann (2009) predicted German unemployment using Google keywords. After the 2008 global economic crisis, this unique online data-based economic prediction tool found substantial correlations between keyword searches and unemployment. Vicente, Lopez-Menendez, and Perez (2022) forecasted Spanish unemployment using internet search and business-confidence data.

5. EXPERIMENTAL STUDIES

Companies experiment. Horton and Tambe (2022) say digital market testing is cheap and easy. Horton (2016) examined desk-hiring algorithms. Technical employment vacancies with recruiting advice filled 20% faster than the control group without displacing non-recommended candidates. In a LinkedIn experiment, Gee (2022) found that more information increased job application completion by 1.9 percent and 6 percent for women.

Application of the Analysis to Shine jobs Data

Shine Jobs tests job-seeker-employer ties. Companies without candidate data risk frictional unemployment. especially for soft skills. Prospective employee information is expensive (Stigler 1962), and inaccurate knowledge can lead to suboptimal equilibria (Spence, 1974; Fang and Moro, 2011). Worker-employer communication enhances labor markets. Grosh et al. (2022) randomized Jordanian labor market matching. Education- and psychometric-based job matching reduced search costs. According to the survey, 28% declined interviews and 83% refused or resigned job offers. Joblessness may cause Indian unemployment. Randomized control trials balance job seeker-employer knowledge. Assess job applicants' non-cognitive skills. In a previous poll, Indian companies hiring new engineering graduates appreciated teamwork, reliability, leadership, passion to learn, creative thinking and problem-solving, and specific knowledge and technical skills. Two of three employers deemed most of these talents "very" significant, but were only "somewhat" satisfied with graduates' competencies (Blom and Saeki 2011).

Frictional unemployment cannot be removed without data. Many empirical research have employed "big-five traits," a psychological method for evaluating personality traits, to explain US and European employment likelihood and pay, expanding global knowledge of how non-cognitive elements affect labor market results. The World Bank's STEP surveys contain the big-five personality test (Pierre et al. 2021). Non-cognitive talents' employer perceptions are unknown. The experiment analyzes how non-cognitive talents effect employment. Research should determine what candidate data organizations need and how filling gaps improves skills-matching. To match people to jobs, organizations need non-cognitive skill data. Shine data reveals how non-cognitive skills effect job searches.

Additional Uses of Online Job-Portal Data and Job-Search Platforms

Beyond the five above, big data can improve labor market outcomes. As stated below, online job-portal data and job-search platforms increase skills-matching and provide policy-relevant data.

Understanding the Emerging Skills Requirements of New Technologies

Technology is transforming businesses and workers. Technology creates non-traditional jobs. Job titles may change competence. O*NET is updated regularly by the US Department of Labor. It lists work obligations, talents, and competencies. O*NET randomly samples occupation-specific firms and individuals. This database benefits from real-time job-portal data on opportunities, requirements, and task scopes. Classifying skills and aligning them to the National Skills Qualification Framework can improve training relevance in India. Text analysis links skills to new jobs. Similar skill statements help classify deceptive occupations. "Computer programmer" can mean "application developer," "web programmer," "web designer," etc.

Advanced Matching Services for Employers and Job Seekers

Machine learning-based text analysis matches skills and trains workers in high-demand skills. Online job portal algorithms notify qualified candidates of new openings, saving employers and job seekers money. Algorithms and websites can help firms describe technical and non-cognitive skills needed for the job. Content-based matching helps diverse job seekers. Non-cognitive talent data could improve job candidate data. Interviews evaluate non-cognition. Encourage employers to find and evaluate job candidates' non-cognitive abilities to save interview time. LinkedIn and other job-matching services have had similar success (Gee, 2022; Horton, 2016).

6. CONCLUSIONS

Online job-portal data research promotes labor economics and workforce skills development policy and academia. These figures are more frequent and varied than employer and workforce surveys. Online job portals track employers' talents and job seekers' economic impacts. Big data helps companies and governments predict labor skills demand. The study above found five key findings. Government labor policies should use online job-portal data. Governments sample employer-employee surveys. Traditional surveys examine labor market trends and skill shortages too rarely and slowly. Real-time big data analytics improves decision-making on statistically neglected issues. Policymakers use surveys. Corporate job-portal statistics aren't surveys. Employers' needs, constraints, and transaction costs minimize frictional unemployment and labor market inefficiencies. Job-portal data reveals skill gaps. Policymakers need new employment classifications and skills data for fast-changing technologies. Demand-driven training may use job-portal data.

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