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AI Impact on Employment in India: A Task-Exposure and Scenario Analysis

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ABSTRACT: The impact of AI, in particular generative AI, on employment patterns globally is quite different from that in India due to the country's prevalent informal and agricultural sectors. In this paper, a sector-specific task-exposure index for India is constructed based on employment shares in the PLFS and an occupational-exposure model from the international literature and is subjected to three scenarios of displacement. Estimates show that roughly 15 percent of India's total working population are in occupations that are "materially impacted" by AI in the short run, encompassing the services, IT-BPM, finance and clerical occupations, rather than the agriculture and construction sector. It is only under moderate assumptions, however, that net job displacement is relatively small overall (around 1.5 to 6 jobs per 100 workers, across scenarios) and significantly greater for routine-cognitive, white-collar and urban, young workers. The paper recommends building policy that focuses on the support of reskilling, AI-complementary education, and social protection as crucial measures in policy, instead of restricting adoption.

1. INTRODUCTION

In each era of general-purpose technology, the question is, will machines take jobs? Or will they make jobs? In the past, automation has proven to have a mixed impact on the number of jobs: it was observed that jobs that have been lost have been replaced, and that many jobs have been created – on average. This particular surge of AI works in different ways because it will be able to carry out non-routine, cognitive tasks like writing, coding, translating and analyses; these types of tasks have long been believed to be impervious to automation. An early study on the U.S. occupations found that almost half of the jobs could be technically automated via computers [2] and a more recent research on big language models suggests that most workers would find between 10 and 20 per cent of their work content amenable to computerisation and another 10 to 20 per cent over 50 per cent [3]. According to the International Monetary Fund, around 40% of worldwide jobs is vulnerable to AI and this rate is higher in advanced economies and lower in emerging economies, but lower preparedness as well [4].

India is a special case and not just for the reason below.India is in fact, a special case: It is the most populous country in the world, has a youthful population requiring to be absorbed into productive jobs in the labour market and also has a dual labour market. The PLFS 2023-24 revealed that over half of Indians still held jobs in agriculture and a majority of those employed made informal arrangements or self-employed [6]. Concurrently, India has a massive IT and business-process services industry with more than 5 million employees and immediate impacts from AI on productivity.Running parallel to this is India's IT/services industry and its business process services industry which are globally important, and work with more than 5 million people, exposed to productivity transformations through sheer usage of AI. The country thus has a double threatening AI development—both because it has a large informal job base, which is lowly, and also because it has a small formal base, with high wages and aspirations, that is highly exposed to AI.

This paper aims at answering three research questions: The first question to ask is which are the most vulnerable areas of the Indian economy with the possibility of changing tasks due to AI. Second, what would the potential size of net employment outcomes be for alternative scenarios of adoption? Thirdly, what policies are proposed? The contribution of the paper is the

development of a transparent, replicable framework of exposures and scenarios for employments in India, and lays the foundation for regular updating as new labour data become available.

1.1 Motivation.

The conversation around AI and work in India vacillates between the extremes of either overpromising or under-promising these technologies' potential. Another camp believes AI should be replacing the job of service-based growth and a generation of young people will emerge who cannot find jobs as their entry-level career options are eliminated by AI. The other side of the argument is that AI will contribute to such an increase in productivity that the number of jobs created will offset the number lost. The two views are not typically backed by a clear picture of where exposure is in fact. The employment structure of India is different from that of the more developed countries on which most of the exposure studies have been based [2, 3] and therefore their results have to be treated with caution for use in India. Treat everyone on a farm or worker in the construction industry and worker in the software testing industry the same, and it's not informative. Therefore, adoption of a 'sector-weighted approach' beginning with the existing employment picture in India is imperative.

1.2 Research objectives and hypotheses.

This study aims at (i) outlining qualitatively the sectoral structure of Indian jobs relevant for the consideration of the exposure to AI, (ii) creating an indicative task-exposure index, (iii) estimating gross task displacement under different AI adoption scenarios and (iv) drawing policy implications for education, skills and social protection. Investigative hypotheses are formulated that are used to guide the analysis.

- **H1:** One key aspect of the exposure to AI is that it has not yet made a significant impact in agriculture and construction in India.
- **H2:** When adoption scenarios are reasonably possible the growth of gross displacement is relatively small as compared to the overall workforce.
- **H3:** Exposed segments are subject to several times the national percentage of displacement.

1.3 Contribution and structure of the paper.

There are three contributions made by the paper. First, it provides an index which is quite simple and reproducible, and could be updated when new labour data become available. Second, it demonstrates how the results change with different values of the input variables, not just a point estimate, based on a sensitivity analysis. Third, it provides a connection between the quantitative outcomes and labour-market institutions and policy design in India. The rest of the paper is presented accordingly. The review of related work is discussed in section 2. In section 3 the methodology is explained. Results and discussion are highlighted in Section 4. Finally, Section 5 is concluded and Section 6 provides a list of references.

2. RELATED WORK

The approach of tasks is used in the modern economics of technology and work. The computer researchers, Autor, Levy and Murnane demonstrated that computers replace routine tasks, but also serve as supplements to non-routine analytic and interactive tasks [7]. Acemoglu and Restrepo thereafter formalized this notion by modelling technology as displace the workers from existing activities and as restore the workers to new activities, depending on the balance between the two, the net employment impact can vary [8]. In their empirical study of the role of the industrial robot in US commuting zones they found that an increase of one industrial robot per thousand has a negative effect on the employment-to-population ratio and wages, demonstrating that robotization can have harmful effects not just in the aggregate but in its impact on individual people by being industrially local [9].

A second strand tells of the polarization of jobs. The study by Goos, Manning and Salomons published in 2019 [10] provides indications of a sharp decrease in the number of middle skill occupations in European countries due to routine-biased technological change, with a higher proportion of high and low paid skills. The potential of the advent of AI is to be able to crawl further into the realm of high skill cognition. Occupational-level exposure measures created by Felten, Raj and Seamans demonstrated that AI exposure is high for knowledge-intensive occupations [11] while Webb created a measure based on the text of patents and demonstrated that AI was doing high-skill work, rather than the low-skill work that was previously thought that robots would do. [12]

Finally a third thread of micro evidence is considered relating to productivity. In large scale customer support, the use of a generative AI assistant increased an average of 14 percent in productivity, and even more so for novice employees [13]. ChatGPT was shown to speed up and enhance the results for professional writing tasks in a random online experiment [14]. The findings indicate that AI can not just replace, but complement, skills deficits to increase a decision maker's advantage over the competition.

A fourth line emphasizes the aspects of demand and structure. The effects of automation on employment within an industry will depend on the elasticity of the industries demand, Bessen said, in that industries with elastic demand will have productivity gains that will lead to an increase in output production, thereby sparing jobs. In developing economies Rodrik raised a concern about premature deindustrialisation that means fewer workers are needed in manufacturing than in a more traditional industrialised development [16]. This is a concern in India because AI now poses a risk of replacing some of the services jobs on which depends the hope of a shift in the economy's structure. Lastly, Acemoglu macroscopes the limited scale of near-term aggregate productivity gains from AI because a small fraction of tasks can be economically-rewarded with automation [17].

Thus, there is a gap in the literature. The majority of exposure studies are designed for advanced countries, which report on formal occupations, and few studies attempt to integrate exposure into a practical and manageable (simple: sector level) model applicable to the well-known agricultural oriented, informal, economy in India. This paper makes an attempt to fill this gap.

2.1 Emerging economies and the Indian setting.

Such is the majority of the empirical evidence reviewed above, that it originates from the international arena (most from the U.S. and Europe), where occupation categorization is formal, firms are large and records are detailed. There are three differences between emerging and other economies. This is related to the larger proportion of jobs in low productivity self-employment and agriculture, thus the jobs that can be undertaken using software will be smaller. Adoption depends on the cost of the factors of production, in particular on the cost of capital compared to that of labour; where labour is abundant and cheap, firms might not be able to make profit on automation of many processes [9], [17]. There is also uneven exposure to digital infrastructure and skills, meaning that the adoption of the digital infrastructure may not happen at the same rate within each region or company. The immediate impact of AI on India would largely relate to the percentage of their workforce working in the 'digital economy' rather than at the average level of the country.

The past experience of technological change in India is relevant. The boom in IT and business-processing services resulted in many jobs for graduates that lacked comparable jobs in manufacturing, consistent with the pattern of 'late-deindustrialisation'* described by Rodrik [16] which was also observed in the UK.In the UK, as in the rest of the world, jobs at the graduate level increased rapidly without comparable manufacturing jobs—a pattern that is described as 'late-deindustrialisation' by Rodrik [16]. This trend has resulted in the formal services sector being particularly significant as an educational destination for the young. With this reduction in labour per unit of output of services, the policy of educated labour absorption via services exports is impacted more than the policy of unskilled labour absorption via agriculture and construction. For this reason, this conceptual correspondence between structural transformation [16] and task based exposure is the basis for the chosen design for the sector level in this paper [8, [11]].

2.2 Informality, gender and skills.

Unlike formal sector studies, informality is a factor that makes it look different when it comes to the impact of AI on workers. Informal workers, who are usually unprotected by employment contracts or severance and social insurance, can often lose their jobs that leads to a correspondent reduction in their incomes [1]. As displaced workers face new high-productivity jobs, task-based models predict that workers transfer to the lower productivity task if the new high productivity task is not created fast enough [8] and in a labour market where there is a large informal sector, the displaced workers move to informal jobs, or become informal self-employed. This is the reason that unemployment figures are a poor measure of the impact of AI on the labour market and why headcount measures should be complemented with metrics of working conditions, like hours worked and wages.

There are 2 ways that skills are important. The performance of less experienced workers may be better AI-tuned than that of more experienced workers, as seen in customer-support and writing tasks [13, 14]. This can help to close skill gaps in companies. However, if firms have fewer high-skilled workers they will be able to do the work a person who is learning might

have done before, more low skilled workers may be left out of the game. The net impact on youth then is unclear and dependent on the elasticity of demand for the output [15]. There's one more layer, that of gender. An occupation based exposure measure [11] suggests that women could be exposed to higher levels than men in the formal economy, do to the high concentration of females in clerical, support, and routine administrative jobs, and lower levels of female male participation in the wider economy means less opportunities are available for the AI revolution. These connections are reasonable but would need the data at the occupancy level to be subjected to a rigorous test; this is missing from this paper.

2.3 Synthesis.

The pertinent literature, when put together corroborates four propositions that can form the basis of the present study. Firstly, there is a difference between exposure and displacement, and adoption, cost and demand are the factors involved in displacement [8] [15]. Second, there is variation in the effects by occupations/skill group [10, 12]. Third, it can be argued that in the short term aggregation productivity effects can be quite small [17]. Finally, the economic structure – the third factor – shapes the result [16]. This analysis of the next section extends these propositions by considering a weighting across the employment structure and a consideration of different outcomes of adoption.

3. METHODOLOGY

3.1 Research design.

The research design was in the form of secondary-data, analytical. Does not depend on a main survey. Rather, it uses national employment structure data to calculate a back-calculated exposure "scenario" index and estimates from task exposure concepts in the literature.

3.2 Data.

The data on sectors of employment share have been obtained from the PLFS 2023-24 annual report [5] which were rounded to the nearest whole percentage for presentation. The classification has been done in a broad manner as per the following five sectors: agriculture, manufacturing, construction, trade, hotels and transport, and other services (other than IT-BPM, finance, education, health and public administration). Data pertaining to the population of people working in the IT-BPM industry comes from industry reports [6].

3.3 Exposure index.

Taking the idea that the exposure measure relates to the level of occupation from [3,11] and that each sector can be defined using an exposure score e in [0,1] such that the scores indicate the proportion of jobs in the sector that current AI systems can execute or contribute to, each sector is defined in this way. The task content of each sector – low, moderate and high – is applied to score the items in each column, with the lowest score being awarded priority for physical, unstructured, outdoor work (agriculture, construction, etc.), followed by high priority for mixed physical and administrative work (manufacturing, trade and transport) and high priority for cognitive, screen-based work (other services). The aggregate exposure index is an event that involves multiple people.

$E = \Sigma (s_i \times e_i)$,

where, s_i indicates the proportion of jobs in sector i and e_i the rating of the exposure of that sector. The interpretation of E is the number of task-exposed jobs/100 (FTE) workers.

3.4 Scenarios.

Don't misjudge things; being exposed isn't being evacuated. Three realisation rates r = 10, 25 and 40 percent are used to simulate, akin to the task-based view where losses can be offset by taking on new tasks [8] and the argument of demand-elasticity [15] about new tasks that reinforce existing realisations. The gross displacement (D) is given by the product of D and r. These are NOT forecasts — but scenario assumptions.

3.5 Limitations.

Judgement-based exposure scores need to be correlated with the occupational-level data (NCO codes) and with employers' questionnaires. The framework does not account for informality specific adoption barriers, regional differences and general

equilibrium effects. Results, therefore, are to be considered indicative and are only intended to help guide discussion — not to forecast actual job numbers.

3.6 Rationale for the scoring criteria.

The assignment of an exposure score was made with regard to the typical task bundle for each of the sectors and three questions. How much of the work is physical, outside the doors, unstructured, like farming and construction, where their current application in this category is limited thus far and doesn't have all the capabilities to provide direct substitution to the work? Secondly, what are the specific percentage of information processing, communication, drafting, coding/analysis, which the large language models are likely to impact on [3]? Thirdly, what proportion is facing customers and necessitates them, customer, or local situation? Those sectors that are predominantly population density of the second type and density of neither the first, nor the third receive better scores. The agriculture score of 0.05 indicates that the occupations last seen are limited to advisory and market information. Another service group with 0.40 indicates that the presence of many service occupations that involve coping with face-to-face situations, e.g. in educational and health units, counterbalances the number of jobs that are screen-intensive, and rely primarily on reading and writing.

3.7 Sensitivity analysis design.

Questions about the robustness of the conclusions test the study as the scores are from judgement. Three scenarios are used that are different from the base scenario. For a low-exposure variant, each time the score is reduced by 20 percent. A high exposure variant increases each of the scores by 20 per cent. It boosts the service margin to 0.50, and the trade and hotels and transport to 0.25, giving a world in which AI spreads faster through customer facing and back office jobs. There are twelve possible outcomes; each one of the variants is linked to the three realisation rates listed above in section 3.4. To determine if the primary findings – concentration in services and moderate aggregate displacement – are applicable over a reasonable range of assumptions.

3.8 Reproducibility and ethical considerations.

Published statistics and stated assumptions have been used throughout the calculation of all input data; likewise all calculations have been made using the simple formulae in Section 3.3 and 3.4, which mean that all figures could easily be inserted into a spreadsheet to reproduce the results. No human participants are involved in the study and the data used are only aggregate publicly available data, thus there are no concerns raised about consent or privacy issues. The author states that exposure scores are his personal opinion, not measurable results and encourages readers to replace his scores with their own for alternatives.

4. RESULTS AND DISCUSSION

4.1 Sectoral exposure.

Table 1 shows the shares of employment, assumed exposure scores and their contribution to the index for each sector.

Sector	Employment share (%)	Exposure score (e)	Contribution (per 100 workers)
Agriculture	46	0.05	2.30
Manufacturing	11	0.25	2.75
Construction	13	0.10	1.30
Trade, hotels and transport	17	0.20	3.40
Other services (incl. IT-BPM)	13	0.40	5.20
Total	**100**		**14.95**

Table 1. Task-exposure index for India (author's calculation based on [5]; scores are author's assumptions).

The overall exposure is around 15, which corresponds to approximately 15 workers' tasks comprising each 1%.The overall exposure is close to 15, or roughly 15 workers' tasks each of 1% exposure. Other services have not only the smallest

percentage of workers, but they also have the greatest exposure (around 35 percent) while agriculture has the highest percentage of workers (45 percent) and the smallest percentage of exposure (15 percent). This verifies the dual-integrity that India has less aggregate exposure than the approximate 40 percent rate of the world economy, primarily due to its agriculture dominance, and the agriculture industry's construction dominance in comparison to other emerging market economies' approximately 40 percent global aggregate exposure as reported in the IMF [4].

4.2 Scenario results.

Exposure to gross displacement is shown in Table 2.

Scenario	Realisation rate (r)	Gross displacement per 100 workers
Augmentation-led	10%	1.5
Balanced	25%	3.7
Displacement-led	40%	6.0

Table 2. Scenario estimates of gross task displacement (author's calculation, E = 14.95).

In the displacement-led scenario gross displacement is approximately 6 per 100 workers and this is excluding the new task and demand effects. This gives further proof of the possible slow and reasonable impact on aggregate [1, 17]. First order risk isn't then mass unemployment, it's a compositional shift.

4.3 Distributional implications.

The exposure is focused only at exactly where India's aspirational formal jobs are. The most vulnerable are IT-BPM, back-office, clerical and customer support personnel, and basic coding. Generative AI's effect on the productivity of novice workers, whether it increases or decreases it, can have two sides: it can elevate the productivity of new employees, but it can also enable companies to make fewer provitious first-round hires to accomplish the same work. Graduates have benefited from the services-led growth in India more than other segments in past rounds of automation, targeting manual jobs.As the majority of AI jobs are delegated to high-skill jobs, graduates are more vulnerable than others when compared to past wave of automation, which was to manual jobs. Clerical and assistance occupations are also a good deal more prevalent among female respondents than are other occupations, and this needs further empirical testing as to its relevance for gender.

4.4 Structural transformation.

Failure of the manufacturing sector to absorb excess labour [16] and a partial automation of services puts India at the risk of a double squeeze to the formal job creation. If workers are displaced from labour market services, they will not easily find new work in agriculture or construction because the pay is lower, so the margin of adjustment is likely to be in the informal sector where there is self-employment rather than employment. Meanwhile, small businesses can benefit from AI complementarity in boosting productivity, vernacular-language public service, health diagnostics, and the agri-advisory process, or those access and skill enhancements could lead to inclusivity improvements [3] [8].

4.5 Policy implications.

Education and training systems should adopt a skills shift from rote and routine, towards skills that use problem solving, can utilise data and can be complemented by the use of AI for reskilling for peoples in the mid-range of their career. Secondly, extending affordably, to a large base, public digital infrastructure and access to affordable AI means complementing (not replacing) rather than competing with. Third, social protection, including portable benefits, unemployment benefits and/or credit for transition, should be boosted for workers in transition. Fourth, labour statistics could be further enhanced to allow tracking of the effect of AI via occupation-level data, as is the current exposure index, which is based on judgemental scores. Reducing the number of children placed for adoption is not advised, since the benefits of such a outcomes on productivity are tangible, and the overall displacement risk seems small when compared to the benefits.

4.6 Sensitivity analysis.

Gross displacement per 100 workers is presented for the twelve combinations listed in Section 3.7 (excluding “all 0”).Table 3 shows gross displacement by combination of 12 combinations (minus "all 0").

Variant	Aggregate exposure (E)	r = 10%	r = 25%	r = 40%
Low exposure (scores × 0.8)	11.96	1.2	3.0	4.8
Base case	14.95	1.5	3.7	6.0
High exposure (scores × 1.2)	17.94	1.8	4.5	7.2
Services-heavy	17.10	1.7	4.3	6.8

Table 3. Sensitivity of gross displacement per 100 workers (author's calculation).

The results are stable with a correct meaning. In terms of gross displacement by outcome, there is a wide range from 1.2 to 7.2 per 100 workers, with the realisation rate as the major determinant, not the exposure scores. Even the most pessimistic scenario results in numbers of people displaced less than 8 per 100 workers that are offset by job creation [8]. Total exposure for the services-heavy variant would be a bit more than 63 percent from other services and trade, further reinforcing the concentration result. It imply that the sources of variation due to uncertainty about how fast a firm is going to adopt are larger than the uncertain scores of the selected sectors, and thus to measure a firm's actual speed of adoption is more valuable than to narrow down sector scores only.

4.7 Sector-level displacement.

The balanced scenario is broken down by sector in Table 4.

Sector	Exposure score	Displacement per 100 workers in the sector	Contribution to national displacement (per 100 workers)	Share of total (%)
Agriculture	0.05	1.25	0.58	15.4
Manufacturing	0.25	6.25	0.69	18.4
Construction	0.10	2.50	0.33	8.7
Trade, hotels and transport	0.20	5.00	0.85	22.7
Other services (incl. IT-BPM)	0.40	10.00	1.30	34.8
All sectors			**3.74**	**100.0**

Table 4. Sector decomposition of gross displacement, balanced scenario (author's calculation).

If you focus on the view within the sector, the message is different. The displacement rate of workers in other services is 10:100; close to eight times higher than the rate for agriculture and about 2.7 times higher than the national rate of 3.7. Manufacturing and trading activities are in the middle implying they involve both physical and administrative activities. However, in absolute terms, agricultural contributions in terms of displacement remain some 15 percent of the national total due to the high number of workers they employ and a small impact on a very high number is not insignificant. This emphasises the importance of taking severity and extent of exposure into account when developing policies.

4.8 Assessment of the hypotheses.

Results in support of all three hypotheses, with qualifications. Workers in other services are 13 percent less exposed on the job than workers in H1, and they make up 35 percent of that exposure, while the agriculture industry has 46 percent of all workers but only 15 percent of the exposure—however, trade, hotels and transport is clearly a second important concentration. No combination in Table 3 results in a greater gross displacement>7.2/100 workers. The displacement rate in services is approximately 2.7 times the national average in all scenarios, but depends directly on the assumed rates of exposure, and should only be interpreted as the outcome of the rate of exposure scoring than as an independently measured fact. The verification of H3 would rely on data at the level of the occupation(s) being studied of actual job postings, hiring and wages.

4.9 Discussion by labour-market segment.

The overall statistics mask four distinct groups, which have very different prospects.

- **IT-BPM and back-office services.** This is the segment that has been exposed the most and is most dependent on entry level hiring. The most common among them are carving up the available tasks into routine coding, testing, documentation, voice and chat support, areas where language models can prove helpful [3] [13]. More likely, there will be retraining or deoptimizing the skills of new hires and a gradual shift toward designers, integrators, to whom the clients come and who are responsible for the overseeing of the functioning of AI systems. As for the elasticity of the output demand, firms with elastic output demand may not require to change their workforce volumes much although they would have to increase output per worker [15].
- **Manufacturing and logistics.** Exposure is primarily related to planning, quality inspection, inventory and supply chain software, and not the shop floor substitution. This impact will likely more reflect changes in job profiles for the supervisors and people working in the office, rather than the massive loss of production jobs [9].
- **Micro, small and medium enterprises and the self-employed.** If available and skilled, AI tools could complement the effort of these firms for accounting functions, marketing, translation, and communicating with customers, potentially boosting productivity, without requiring the adoption of such high-tech solutions.Access to AI tools and expertise may increase productivity for these firms where tasks such as accounting, marketing, translation and comms with customers are concerned. The danger is two-fold; it is that firms who can use these tools will benefit and build on them, but those who cannot will fall further back.
- **Agriculture and construction.** The potential direct displacement is relatively limited, whereas if provided in the locals' language and disseminated through convenient channels, advisory services, price information and weather-based decision support can boost incomes. The real problem here is not rather than substitute access, but access and trust.

These indicate that the greatest threat to the employment of the Indian worker is a altering of the entry to employment opportunities and their earnings in specific segments and the most important opportunity is in providing complementing the productivity of small producers, who currently do not receive any professional support [8], [17].

4.10 Policy framework.

Table 5 correlates the recommendations in Section 4.5 to target groups, instruments and indicators which are available for monitoring.

Policy area	Target group	Instrument	Indicator to monitor
Skills and education	Graduates, entrants to IT-BPM	AI-complementary curricula, apprenticeships, modular certification	Share of graduates in skilled jobs within one year
Mid-career reskilling	Workers in exposed services roles	Portable training credits, employer-linked short courses	Participation and re-employment rates
Access to AI tools	MSMEs, informal workers	Shared digital infrastructure, local-language interfaces	Share of MSMEs using AI-enabled tools
Social protection	Displaced and transitioning workers	Portable benefits, transition income support	Duration of unemployment, earnings change
Labour statistics	Policymakers and researchers	Occupation-level data, linked hiring and wage records	Availability of AI-exposure series by occupation

Table 5. A monitoring-oriented policy framework (author's synthesis).

By focusing on indicators, the framework is deliberately designed, as is the exposure index in this paper, so that it will be replaced over time with indicators based on outcomes. Where the pace of AI adoption is uncertain, having a policy with measurable indicators becomes important as there is a need to modify the policy as evidence builds up over time [17].

4.11 Implications for research and practice.

The research shows that an exposure index for developing countries should be created based not on the occupational databases from affluent economies, but rather based on the makeup of the national labour force. The results suggest that in the context of employment practices in firms, workforce planning should be seen as a job-level process engaging with the need to prepare workforce for new institutional roles in oversight, data and client engagement [8] while firms should pay attention to the development of the skills of their existing staffs rather than replacing them. For policy makers the findings suggest a focus on safeguarding transitions and ensuring they have a greater reach, as the overall risk seems less than significantly high, but the distribution risk seems more serious.

5. CONCLUSION

In this paper, transparency across the sectors was provided by identifying a sector-based exposure index and uses scenario analysis to gauge the potential effect of AI on jobs in India. About 15 percent of the total value of employed workers' activities seem to be open to them, clustered in the services and IT-BPM sectors, and agriculture as well as construction, fairly sheltered. The aggregate effects are moderate (between 1.5 and 6 workers are displaced per 100 workers, depending on the scenario) while the distributional effects are severe: in the scenarios considered, they are large and significant for young, educated, white-collar workers, and for entry-level service occupations. Key policy message: India is not facing a mass unemployment problem, it is faced with a challenge of transition and quality of jobs – investment in reskilling, access to AI and social protection will be key to either expanding or decreasing the inequality.

The scores of exposure needs to be further validated with occupation level (NCO) data, a firm level survey in IT-BPM and MSMEs and studying the differences between gender levels and regional differences and differences in the informal sector. The conclusions assume that they are conclusions drawn by a valid approach and, therefore, indicative of the data extrapolated.

Summary of main findings. There are four points of outcome which are remarkable. This is mainly due to the weight of agriculture and construction and means that, despite the average per 100, task exposure is only around 15, lower than the average for the world. Second, exposure is localized in services where exposure is generated by 13 percent of workers, but accounts for 35 percent of the potential exposure. Third, the gross displacement in each scenario/sensitivity combination remains fairly constant in the 1.2 percent to 7.2 percent range per 100 workers. Fourth, in the larger services segments that are exposed, the displacement is around 2.7 times that suffered by all workers.

Limitations. The study is based on judgement-based exposure scores, constant employment shares and uniform realisation rates by measured sector, as well as a model that does not posit a wage function or a change in tasks within the firm, across industries and size or region. It's a thoughtfully approach to considering the magnitude, so it's not a prediction. Results should be interpreted in conjunction with other evidence in the field on hiring, wages and productivity, which will be published as it comes in.

Concluding remark. Leaving aside the possibility of a "sudden die-off" of Indian jobs brought about by AI, there is a possibility that it subtly changes the nature of the first job for any profession and how small producers compete. Any combination of skills, access and protection supplemented by a policy that is based on measurable indicators has the best potential to achieve widespread benefits from exposure.

REFERENCES

[1] D. H. Autor, "Why are there still so many jobs? The history and future of workplace automation," J. Econ. Perspect., vol. 29, no. 3, pp. 3–30, Summer 2015, doi: 10.1257/jep.29.3.3.

[2] C. B. Frey and M. A. Osborne, "The future of employment: How susceptible are jobs to computerisation?," Technol. Forecast. Soc. Change, vol. 114, pp. 254–280, Jan. 2017, doi: 10.1016/j.techfore.2016.08.019.

[3] T. Eloundou, S. Manning, P. Mishkin, and D. Rock, "GPTs are GPTs: Labor market impact potential of LLMs," Science, vol. 384, no. 6702, pp. 1306–1308, Jun. 2024, doi: 10.1126/science.adj0998.

[4] M. Cazzaniga et al., "Gen-AI: Artificial intelligence and the future of work," IMF Staff Discussion Note SDN/2024/001, Int. Monetary Fund, Washington, DC, USA, Jan. 2024, doi: 10.5089/9798400262548.006.

[5] Ministry of Statistics and Programme Implementation, "Annual Report: Periodic Labour Force Survey (PLFS), July 2023–June 2024," Govt. of India, New Delhi, India, 2024. [Online]. Available: https://mospi.gov.in (no DOI assigned).
[6] NASSCOM, "Technology industry in India: Strategic review 2024," NASSCOM, New Delhi, India, 2024. [Online]. Available: https://nasscom.in (no DOI assigned).
[7] D. H. Autor, F. Levy, and R. J. Murnane, "The skill content of recent technological change: An empirical exploration," Q. J. Econ., vol. 118, no. 4, pp. 1279–1333, Nov. 2003, doi: 10.1162/003355303322552801.
[8] D. Acemoglu and P. Restrepo, "Automation and new tasks: How technology displaces and reinstates labor," J. Econ. Perspect., vol. 33, no. 2, pp. 3–30, Spring 2019, doi: 10.1257/jep.33.2.3.
[9] D. Acemoglu and P. Restrepo, "Robots and jobs: Evidence from US labor markets," J. Polit. Econ., vol. 128, no. 6, pp. 2188–2244, Jun. 2020, doi: 10.1086/705716.
[10] M. Goos, A. Manning, and A. Salomons, "Explaining job polarization: Routine-biased technological change and offshoring," Am. Econ. Rev., vol. 104, no. 8, pp. 2509–2526, Aug. 2014, doi: 10.1257/aer.104.8.2509.
[11] E. W. Felten, M. Raj, and R. Seamans, "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses," Strateg. Manag. J., vol. 42, no. 12, pp. 2195–2217, Dec. 2021, doi: 10.1002/smj.3286.
[12] M. Webb, "The impact of artificial intelligence on the labor market," SSRN Electron. J., Nov. 2019, doi: 10.2139/ssrn.3482150.
[13] E. Brynjolfsson, D. Li, and L. Raymond, "Generative AI at work," Q. J. Econ., vol. 140, no. 2, pp. 889–942, May 2025, doi: 10.1093/qje/qjae044.
[14] S. Noy and W. Zhang, "Experimental evidence on the productivity effects of generative artificial intelligence," Science, vol. 381, no. 6654, pp. 187–192, Jul. 2023, doi: 10.1126/science.adh2586.
[15] J. Bessen, "AI and jobs: The role of demand," NBER Working Paper 24235, Nat. Bureau Econ. Res., Cambridge, MA, USA, Jan. 2018, doi: 10.3386/w24235.
[16] D. Rodrik, "Premature deindustrialization," J. Econ. Growth, vol. 21, no. 1, pp. 1–33, Mar. 2016, doi: 10.1007/s10887-015-9122-3.
[17] D. Acemoglu, "The simple macroeconomics of AI," Econ. Policy, vol. 40, no. 121, pp. 13–58, Jan. 2025, doi: 10.1093/epolic/eiae042.