Research Paper IMPACT FACTOR VALUE : 5.983 | E-ISSN NO : 2455-295X | VOLUME : 11 | ISSUE : 12 |DECEMBER 2025

ARTIFICIAL INTELLIGENCE AND THE FUTURE OF EMPLOYMENT: A SOCIOLOGICAL STUDY OF YOUTH IN INDIA

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ABSTRACT:

Although Artificial Intelligence (AI) is revolutionizing the world of work, its social impact on the young population in developing economies has not been much explored. This descriptive, survey study examines the perceptions of the implications of AI for work amongst Indian youth aged between 18 and 29; awareness of AI technologies; and readiness for an AI-mediated labour market. A structured questionnaire was used to obtain data from 150 persons and Statistical Package for Social Science (SPSS) was used for analysis using frequencies, percentages and chi-square. Unusually high but uneven spread of awareness: 78 per cent have moderate or high awareness, 55.3 per cent are concerned about job security. Just over one-third (38.7 per cent) have developed skills in the use of AI, and urban youth are much more likely than rural youth to have developed these skills, with almost all of them having done so. When it comes to which areas are at the greatest risk, the respondents see customer service and manufacturing are most vulnerable, while a third believe that AI can be transformative, not just destructive. Tackled from the lens of risk society and cultural and precariat perspectives, the research makes the argument that there is a social distribution of employment anxiety related to AI, and that unequal access to digital capital and not only technologies should be the target of policies.

KEYWORDS:

ARTIFICIAL INTELLIGENCE, EMPLOYMENT, YOUTH, INDIA, DIGITAL DIVIDE, SOCIOLOGY OF WORK, UPSKILLING.

PAPER ACCEPTED DATE:	PAPER PUBLISHED DATE:
25th December 2025	30th December 2025

1. INTRODUCTION

Artificial intelligence is one of the technological advancements that has captured the public's eye in recent years more than any other. Today, machine learning systems compose text, read medical images, vet resumes, and craft software code, respond to customer queries, and more. Since 2022, there have been generative models extending automation beyond routine manual/clerical tasks to ones long thought to be the reach of educated professionals (Eloundou et al., 2023). The range of estimates of how much disruption will be seen is wide, from the dramatic claim by Frey & Osborne (2017) that nearly half of occupations are at risk of computerisation since the level of automation will be more about change than loss of jobs (Arntz et al., 2016; World Economic Forum, 2023).

The setting of India is particularly suggestive for exploring these issues. It has one of the world's largest youth populations and the demographic dividend that is emphasised by policy makers relies on either finding a productive job for the millions of young entering the labour market annually or on the other hand, it does not find one. As per the India Employment Report 2024, India's youth is an underrepresented population in the ranks of the country's unemployment, and educated youth are especially vulnerable to unemployment (ILO & Institute for Human Development, 2024). The periodical Labour Force Survey also shows a significant informal sector, and gender disparities in labour force participation (MoSPI, 2023). This precarious scenario is where AI has come, being marketed as a national opportunity by a government body (NITI Aayog, 2018) and framed in the media as a wonder as well as a danger.

There are three significances of the study. In the academic sense, it provides a sociological interpretation of AI and work, where the majority of studies have been focused on an economic model. Cooperatively, it provides insights into youth awareness, anxiety and readiness to educators, employers and policy makers. Socially, it is a reminder of the potential for the inequality of societies that adopt it.

2. REVIEW OF LITERATURE

2.1 TECHNOLOGICAL CHANGE AND THE EMPLOYMENT DEBATE

Since the first industrial revolution, it has been discussed how technology is related to work. However, while routine work has been replaced by automation, non-routine work has been enhanced by it, as argued by Autor (2015) leading to an expansion in employment, even as employment has been polarised and the nature of employment has changed. In the 'second machine age' as

described by Brynjolfsson and McAfee (2014), all the gains that can be associated with the use of digital technologies are large, but unevenly distributed, with those who have limited skills and capital benefitting more than those have more. But it has been buttressed by empirical evidence: Acemoglu and Restrepo (2020) established that introduction of industrial robots led to an employment and wages decline in the local labour market in the U.S.

Another focus of research is on the rate and nature of change. Previously mechanised waves primarily replaced physical work, but cognitive and interpersonal aspects of work remained fairly safe. The difference in contemporary AI is that they can learn from data, generalise across contexts and engage in a variety of tasks to do with language, perception and prediction. This expansiveness explains the unique nature of these anxieties, and also the fact that youth who have been schooled for just this kind of cognitive labor now challenge ideas that learning leads to work.

Some of the scholars emphasize contingence instead. The employment impact of AI is also dependent on demand conditions: In expanding markets, productivity gains could increase employment, while decreased productivity actually could reduce employment in limited markets, Bessen (2019) reports. Based on this, Muro, Maxim and Whiton (2019) show that exposures to automation vary by place, occupation, and demographic population group. While some tasks might sail through, others may require the assistance of higher-skilled workers that are likely to be impacted by AI, as Webb suggests, earlier technologies were limited by their inability to influence the work of more highly educated professionals.AI, on the other hand, is most likely to change the job tasks of higher-skilled workers, with Eloundou et al. estimating that large language models could alter at least some tasks in a very large majority of occupations. All of these studies combined, however, give the sense that the AI transition will not necessarily be life-changing in a negative or a positive way.

2.2 AI AND THE INDIAN LABOUR MARKET

In addition, Indian commentaries highlight the importance of the informal sector, characterized by the absence of contracts, social security, and bargaining power for most workers in the sector (MoSPI, 2023). Technological change is not as much about job being redundant as it is about jobs losing the value of their earnings, a reinforced work done through the platforms and a soft disappearance of jobs of lower levels. AI for youth could be authentication of an event and experience rather than a one-off event, as it is a stealth assault that may develop as the pathway for careers cavities begin.

The question is especially relevant in the context of India progressing on a trajectory of attaining a services economy. The information technology and business-process outsourcing industry have taken up many graduates, and depend heavily on what is essentially routine cognitive labor, the most vulnerable type of labor to be automated (Autor, 2015). Concurrently, NITI Aayog (2018) mentions that AI is one of the areas of growth for Agriculture, Health, Education and Smart Cities and calls for large scale skilling and reskilling. The World Economic Forum (2023) also predicts that there will be significant job change worldwide, and that analytical thinking and creative thinking, as well as technological literacy, are two of the skills that will be in higher demand. It is not clear if India's education and training system will be able to generate such capabilities at volume.

2.3 YOUTH, SKILLS AND INEQUALITY

There are additional layers of gender and locality. Record low inclusion of women in the Indian workforce, restricted in vulnerable jobs, may weigh on a small pool of opportunity on any impact from the technology shock (MoSPI, 2023). Meanwhile, rural youth are regularly attending institutions with fewer labs, fewer teachers and limited Internet access and this curtails access to digital tools before the arrival of the labour market. The fact that these structural conditions indicate that one could not separate perceptions of AI from social location.

Young people are the most immediately affected by changes in the labour market and are entering the market without a seniority list or job security. According to ILO and Institute for Human Development 2024, India's youth has seen a significant improvement in their educational levels and qualification, which is twice the pace of the generation of appropriate job opportunities, creating an aspiration gap. Standing (2011) describes these as an "insecure world of contract" and an “uncertain future” which creates a ‘precariat'. Digital inequalities also play a role in this: a difference in device, connection and quality training is observed between income groups, regions and gender. There is a vast amount of research on AI's impact on the economy, but there's limited research on how the preparedness of Indian youth differs by social groups and how they experience AI processes.

3. THEORETICAL FRAMEWORK

There are a number of sociological perspectives to which survey responses can be attributed. However, Beck (1992) has stressed that manufactured risks are inherent in the modern societies, and today's societies increasingly hand over responsibility for them to individuals. When applied to a young person, the message is to ‘reskill' for AI, whereas in practice, it's a structural threat not a personal threat. The resources for coping are also unevenly distributed, within Beck's definition of individual responsibility, resulting in anxiety.

Secondly, Bourdieu's (1986) notion of capital makes sense of this difference in preparation. Economic, cultural and social capital determines who has access to coaching, who heard of emerging opportunities and who has a set of dispositions that align with the needs of workplaces that rely on AI. Therefore, there is a possibility for urban, educated younger generation to learn to convert capital on skill related to AI more quickly than rural educated young. A similar distinction is made by Castells (1996), who spoke

of labour which is "self-programmable" (capable of continuous learning) as opposed to "generic" labour (easily replaced).

Third, Standing's (2011) concept of the precariat and Braverman's (1974) theory of deskilling and managerial control have the potential of exacerbating insecurity and breaking down skilled work into monitored, fragmentary tasks.Third, and linked, Standing's (2011) concept of the precariat and Braverman's (1974) theory of deskilling and managerial control suggest that AI could worsen insecurity and fragment skilled work into monitored tasks. Fourth, Giddens (1991) clarifies the reflexive project of the self and how individuals make and remodify biographies and career identities in an uncertain world, which is further enhanced by AI. Last but not least, the technology acceptance model (TAM) was proposed by Davis (1989) as it suggests that perceived usefulness and ease of use contributes to adoption, to explain why awareness may not as readily lead to learning when the training is inaccessible. These lenses help support the following hypotheses.

4. OBJECTIVES AND HYPOTHESES

The study pursues the following objectives:

- To assess the level of awareness of AI technologies among Indian youth.
- To describe youth perceptions of AI's impact on job security and employment opportunities.
- To examine the extent of skill acquisition and access to training for an AI-driven economy.
- To identify sectors that youth consider most vulnerable to AI-led automation.
- To analyse whether concern and preparedness vary by place of residence.

Four hypotheses were formulated.

H1: Awareness of AI is moderate to high among most respondents.

H2: A majority of respondents are concerned about job security.

H3: Upskilling in AI-related skills is significantly associated with place of residence.

H4: Concern about job security is significantly associated with place of residence.

5. METHODOLOGY

5.1 RESEARCH DESIGN

The study is descriptive in nature which is suitable when the aim is to describe the nature and distribution of attitudes in a well defined population (Kothari, 2004). For getting quantitative data, a cross sectional survey was used at one point of time.

5.2 POPULATION AND SAMPLE

Young Indians (aged 18 to 29) were targeted in the population which were used as per the accepted definition of youths in national statistics. The samples (n = 150) were selected purposively by imposing quotas to illustrate the gender, level of education, and place of residence. Students, employed youth and aspiring youth from various districts of central India, online, responded. The results are indicative and cannot be statistically viewed as representative of all Indian young people as the sample is not probabilistically drawn.

5.3 TOOL OF DATA COLLECTION

The key variables were operationalised as shown below. The three components of AI awareness – self-reported familiarity with applications, understanding of how AI tools works, and frequency of use – are combined into a composite score that is categorized as low, moderate or high. A statement that AI poses risks to the employment prospects of persons of the respondent's age was agreed in order to capture the Job-security concern. Respondents' preparedness was gauged by whether they had gained skills in AI, and by their perceptions on whether the training is adequate. The place of residence was classified as urban, semi-urban or rural.

A detailed questionnaire was created in three modules: Socio-demographic profile, awareness and perception of AI and Preparedness and skilling. Attitudinal variables were assessed by using a 5-point Likert Scale ranging from strongly disagree to strongly agree with 1 being strongly disagree, 2 being slightly disagree, 3 being neutral, 4 being slightly agree, and 5 being strongly agree. The instrument was pre-tested on 15 respondents, who were not included in the sample, but a few small changes were made in the wording. The Cronbach's alpha level was 0.82 which indicates a good consistency in the perception scale.

5.4 DATA COLLECTION AND ANALYSIS

Collection of data was done over a duration of six weeks by the use of printed forms and an online survey. They all volunteered, informed consent was taken and confidentiality was assured. Out of the questionnaires which were returned 150 questionnaires were complete and valid which were retained for analysis. Coding and analysing the responses involved frequencies, percentages and chi-square tests of independence and significance was set at 0.05.

6. FINDINGS AND ANALYSIS

6.1 SOCIO-DEMOGRAPHIC PROFILE

The profile of the respondents is presented in Table 1 below: Males (52.0%) and females (46.7%) respondents are reasonably evenly distributed through the sample. There are some peaks in the 22-25 age cohort, reflecting transition from education into the workforce (42.0 per cent), and a peak in the 30 to 34 age cohort. There are peaks in the transition from education to labourforce (42.0 per cent on 22-25), and a peak in the 30-34 ageband. Six out of 10 residents are urban dwellers (64.0 per cent), with 15.3 per cent in rural areas. The majority of postgraduates represent the largest educational group (41.3 per cent) while still on college 42.7 per cent of respondents are students.

TABLE 1: SOCIO-DEMOGRAPHIC PROFILE OF RESPONDENTS (N = 150)

Characteristic	Frequency	Percentage
Gender: Male	78	52.0
Gender: Female	70	46.7
Gender: Other	2	1.3
Age: 18–21 years	41	27.3
Age: 22–25 years	63	42.0
Age: 26–29 years	46	30.7
Education: Undergraduate	58	38.7
Education: Postgraduate	62	41.3
Education: Professional/technical	30	20.0
Residence: Urban	96	64.0
Residence: Semi-urban	31	20.7
Residence: Rural	23	15.3
Status: Student	64	42.7
Status: Employed	47	31.3
Status: Seeking employment	39	26.0

6.2 AWARENESS AND PERCEPTION OF AI

Another relationship which was looked into was awareness and education status. The higher awareness toward AI being reported by respondents who were pursuing/post-had gotten a postgraduate and/or professional degree, seemed to indicate that exposure to AI is dependent on the type of institution and course a young person is attending. The discovery confirms that "awareness" is one of the forms of cultural capital, acquired in different ways.

The roll-out of AI into the labor market is easily recognized in absolute terms, bolstering H1. As indicated in Table 2, there was high level of awareness in 36.0 per cent, moderate level of awareness 42.0 per cent and low level of awareness 22.0 per cent. The most common sources for respondents were using AI in social media, recommendation systems and generative tools, as well as chatbots, with social media being the most frequent source of information and not formal education.

There is a great concern over work. Over half of respondents (55.3 per cent) agreed or strongly agreed that AI threatens job security for people of their age, whereas 25.3 per cent disagreed and 19.3 per cent were neutral. This means it is possible to support H2. The impact of AI on employment was divided: forty per cent thought that AI would lead to a loss of jobs, while 25.3 per cent thought it would create new ones, and 34.0 per cent felt it would both destroy and create new. There was also a split among emotional orientations: 38.7 per cent reported that they were ambivalent, 32.7 per cent optimistic and 28.7 per cent anxious.

TABLE 2: AWARENESS AND PERCEPTIONS OF AI (N = 150)

Variable and category	Frequency	Percentage
Awareness: High	54	36.0
Awareness: Moderate	63	42.0
Awareness: Low	33	22.0
AI threatens job security: Strongly agree	31	20.7
Agree	52	34.7
Neutral	29	19.3
Disagree	27	18.0
Strongly disagree	11	7.3
Expected effect: Will reduce jobs	61	40.7
Will create new jobs	38	25.3
Both reduce and transform	51	34.0
Attitude: Optimistic	49	32.7
Attitude: Ambivalent	58	38.7
Attitude: Anxious	43	28.7

6.3 PREPAREDNESS AND PERCEIVED VULNERABILITY OF SECTORS

Respondents who didn't have acquired skills indicated that the lack of affordable courses was the most common reason they didn't acquire them, along with a lack of time with their studies or jobs, and a lack of knowledge of what skills would truly be valued by the employer. Some responded saying that they were concerned about valuing training that could turn out to be irrelevant. The study of the present moment is a study of risk, uncertainty, implications and ambiguity because it's always a decision to make; uncertainty about the future makes preparation itself a risky decision, particularly if you have limited financial margin.

Saucon Valley's gap between awareness and preparedness is quite wide. Just 38.7 per cent of respondents had learned AI skills like 'prompt engineering', 'data processing', or 'programming fundamentals', 32.7 per cent had intended to learn AI skills and 28.7 per cent had not considered it. The training available was also not equally good, with only 29.3 per cent of people considering it 'good', 34.7 per cent ‘partial' and 36.0 per cent describing it as ‘poor' or ‘no'. Respondents then know about AI more frequently than they've been able to learn it.

This sector is most at risk was most frequently cited by respondents as customer service or business-process outsourcing (31.3 per cent), followed by manufacturing (19.3 per cent), IT and software (16.0 per cent) and banking and finance (14.0 per cent). The other responses were much less common, such as with education, creative and media activities, and health-care. Youth align themselves immediately with AI risks and the task based

literature indicates that easily measured tasks are at risk of being performed by youth.

TABLE 3: PREPAREDNESS AND PERCEIVED SECTORAL VULNERABILITY (N = 150)

Variable and category	Frequency	Percentage
Acquired AI-related skills: Yes	58	38.7
Planning to acquire	49	32.7
No	43	28.7
Training access: Adequate	44	29.3
Partial	52	34.7
Inadequate	54	36.0
Most vulnerable: Customer service/BPO	47	31.3
Manufacturing	29	19.3
IT/software	24	16.0
Banking/finance	21	14.0
Education/teaching	11	7.3
Creative/media	11	7.3
Healthcare	7	4.7

6.4 VARIATION BY RESIDENCE AND GENDER

Table 4 cross tabs concern and upskilling according to place of residence. There is a higher worry on job security among semi-urban (58.1 per cent) and rural (73.9 per cent) respondents compared to those from urban areas (50.0 per cent). At this sample size there is no significant difference (χ^2 = 4.41, df = 2, p > .05) between the two groups of data as indicated by a chi-square test, but the direction of the gradient is interesting. When grouped according to gender, 58.6 per cent of the women and 52.6 per cent of men said they had a moderate concern.

Upskilling, on the other hand, is well structured. Almost one-half (49.0 per cent) of urban youth acquired skills related to AI, Rural youth acquired less skills related to AI (13.0 per cent) and Semi urban youth acquired second most (25.8 per cent). This is a statistically significant association (χ^2 = 12.81, df = 2, p < .01), which is consistent with H3. That is, the more anxiety-prone they are, the lower their ability to respond; the more prepared they are, the less anxiety prone.

TABLE 4: CONCERN AND UPSKILLING BY PLACE OF RESIDENCE

Residence (n)	Concerned about job security	Acquired AI skills	Statistical result
Urban (96)	48 (50.0%)	47 (49.0%)	
Semi-urban (31)	18 (58.1%)	8 (25.8%)	
Rural (23)	17 (73.9%)	3 (13.0%)	
Total (150)	83 (55.3%)	58 (38.7%)	Concern: χ^2 = 4.41, ns; Skills: χ^2 = 12.81, p < .01

7. DISCUSSION

The results give a picture of an educated youth generation, but significantly not all of them are equally ready to act when the impact of AI does not meet expectations. While awareness is high, confidence is lower, more than half are worried about jobs and few have got the required skills. These are not the complacencies of individuals, but indications of structural inequalities. According to Beck (1992) the responsibility of adapting to technological change is becoming more individual, irrespective of the equal training or resources. Likewise, Giddens' (1991) notion of reflexive uncertainty can account for the significant share of survey respondents who are not worried or optimistic about the impacts of AI on work.

The distinction between the upskilling opportunities enjoyed by those adopted to become to those who are not, is important because of the framework Bourdieu (1986) introduces, based on his points on social differences themselves. A greater cultural and economic capital amongst urban youth is available as a result of being connected socially and economically, by institutions, by peer networks, and through coaching, and transforms awareness into skill. According to Castells (1996), however, these two classifications also bring into line the issue of whether AI might further perpetuate inequalities. Castells' (1996) contrast between self-programmed and generic labour also suggests that AI may help with reinforcing inequalities. Gender and education also play a role in perceptions, with education labeling women a bit more concerned, and education boosting awareness and expectations.

Job tasks have been found to influence respondents' perceptions of vulnerability across all jobs, particularly routine service jobs (e.g., job tasks literature: Autor, 2015; Arntz et al., 2016). Yet, low recognition of risks for professional and creative jobs might be a function of optimism bias. The anxiety caused by AI is common on the whole, but not evenly so; there is less adaptive capacity. The prominence of social media as the primary source of information also underscores the importance of trustworthy institutional instruction and easily accessible, equitable skill development training courses.

8. RECOMMENDATIONS

On the basis of the results, the following measures are recommended:

- Embed AI Literacy and digital skills as part of the school and college curriculum, focusing on rural and semi-rural schools.
- Increase the size of training programs that are accessible, vernacular and mobile, with public–private partnerships and community digital centers.

- Redeesigning skilling opportunity paths for employees in the sectors that were most worrying, like customer service, BPO and manufacturing.
- Enhance career guidance and labour-market information to help youth understand AI-related change in a realistic way.
- Create social protection and fair transition policies for informal and platform workers to ensure that they are not solely responsible for any transition adjustment.

9. LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

There are some limitations to the research. As the samples are limited to 150 respondents in each, which is not representative of the Indian youth, results cannot be generalized to the larger population of the nation; besides, self-reported perception of labour market performance may be influenced. Cross-sectional design can obtain perspectives of a field at a single stage, in a rapidly changing timeline. Further studies are possible with larger representative samples, longitudinal studies and qualitative interviews, and more systematic comparisons between sectors, castes, genders and regions.

10. CONCLUSION

Crashing the paradigm paradigm is zeroing on examining Indian youth's perception and readiness for an AI influenced future in the world of work. The results from the 150 respondents demonstrate the high level of awareness, broad concern, mixed expectations and lack of preparedness. To be sure, there is a social divide in access to—rather than resistance to—AI-related skills: Youth in urban areas are much more likely to have developed them than those in rural areas, despite the shared anxiety. The nature of the distribution of cultural, economic and digital capital will, therefore, influence the impact of AI on jobs in India as well as the technology itself. Technical change is only half the story of the future of work; the social justice story is the other as seen through a sociological prism. In the era of Artificial Intelligence, policies that can enhance the potential of equitable access to learning, instil the sense of transition and acknowledge structural rather than individual responsibility will be key to leveraging India's demographic dividend.

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