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Beyond the Machine: Indian Workers in the AI Age

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Abstract:

Technological transformation and automation in Artificial intelligence are radically transforming the nature of work in the primary and secondary sectors in India'. To gain a deeper insight into the human factors in technological transformation this review focuses on the effects of technological modernization on both workers and organizations. In particular, it explores the role of morale, and motivation, and mental health during technological transformation, and further observing human factors in resisting obsolescence, digital fatigue, and a natural resistance to the changing nature of working, and technological innovations, and in addition observing human factors associated with damage to reasoning and problem-solving during technological transformation in industry and agriculture. The results reveal that while technical upgrades improve output, they can lead to lower employee engagement and a loss of professional identity if not managed carefully and in agricultural country such as India, where millions are employed in farming and industry, and there is a desperate need for human-oriented approaches to make technological advances and industrial growth sustainable growth with AI. This ensures that growth remains on a positive and equal track for all workers.

Keywords: Artificial Intelligence, Labour Markets, Employee Well-Being, Organizational Change, Agriculture.

Introduction:

India's working-age population of over five hundred million makes it a major player in the labour market globally; with 40 per cent employed in agriculture and 17 per cent engaged in manufacturing (International Labour Organisation [ILO] 2018). The introduction of the Fourth Industrial Revolution has serious ramifications for the economy and society in India. Over the last few years, many industries have adopted AI-based system2s and robots to automate processes. The World Economic Forum indicated that India has strong capabilities to create automation systems and also has increasing levels of AI-based technologies

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including agricultural drones and chatbots, which are beginning to permeate rural areas of India (World Economic Forum 2018; Press Information Bureau [PIB] 2020).

There are many notable issues due to the rapid growth of digital technology including artificial intelligence (AI) and its effects on productivity and work processes in both agricultural and industrial sectors. In what ways do these effects vary between the two sectors? Additionally, how do human factors impact technology changes, such as morale, identity and gender? As these critical questions arise as a result of the rapid advancement of digital technology, there are also many new questions arising. For example, in what way does AI change the shape of productivity and the nature of work processes? Is there a difference between agriculture and industrial manufacturing regarding their effects? Lastly, do human dimensions (e.g., morale, identity, gender) have an effect on technology changes?

The present study addresses these questions by reformulating the author's earlier working paper into a comprehensive research article. The aim of the study is to provide a balanced and evidenced based evaluation of the impact of AI technology on Indian workers. The analysis builds on the findings incorporating literature published between 2015 and 2026.

More specifically, the paper pursues the following objectives:

- To strengthen the theoretical framework by integrating perspectives from labour economics, organisational psychology, and Science and Technology Studies (STS);
- To provide a transparent description of the literature-review methodology;
- To document case studies from Indian agriculture programme and robotics applications in Rajasthan and manufacturing including the Swaraj tractor plant and other automated facilities
- To synthesise sectoral findings through comparative analysis; and
- To discuss implications for policy, labour markets, and future research.

The theoretical framework outlines key concepts from labour economics, organisational psychology, and socio-technical studies. The methodology section explains the literature-review strategy and its limitations. The case-study section summarises empirical examples from Indian agriculture and manufacturing. The comparative synthesis describes how different sectors impact productivity, skills, worker well-being, gender relations, and policy at the same time. The findings from these various sectors are combined to identify areas of commonality among the sectors and also to highlight the challenges facing workers in all sectors. Finally, the synthesis concludes with a summary of the most important findings and suggests future research directions.

Theoretical Framework

For a long time, changes in technology have been involved in the debate about how this innovation affects the labour market. As automation takes over manual jobs and cognitive tasks like completing a simple project, this automation will create new work opportunities that require a higher level of skill and technical proficiency than it has before (Acemoglu & Restrepo, 2019; World Economic Forum, 2019). According to Acemoglu and Restrepo (2019), artificial intelligence and robotics will displace some types of labour in India, but these technologies also create new types of labour (i.e., new jobs) that require a greater number of skills and technology than were necessary for earlier jobs.

Brynjolfsson and McAfee (2014) call this new technological age the "second machine age," and while this era is marked by rapid advances in digital technologies that increase productivity here, it could also lead to a fractured labour market. Finally, as Autor, Levy, and Murnane (2003) note, workers can be seen as bundles of tasks. Workers are moving from performing standard tasks to managing/overseeing these operations and/or performing analytical and/or creative functions due to the use of automated systems to handle standardised or data-driven processes (World Economic Forum, 2019). The transition implies that digital literacy, the ability to interpret data, and the ability to solve complex problems must continue to be learned and developed at an increasing rate.

Though economic analysis is one way of understanding what is happening, the psychological effects of technology transformation on humans are significant, especially when considering that AI can create both positive (increased job satisfaction) and negative (technostress/digital fatigue) experiences in a work environment. There are certainly examples of how the automation of physically taxing or mundane jobs can allow workers to do more meaningful work that leads to increased job satisfaction for workers, allowing them to be more human than they may have been in the past by taking some of the burden off of their data-entry work (Brynjolfsson & McAfee, 2014). For example, Swaraj Tractors has implemented the use of an ergonomic robot to enable employees to focus on supervisory positions rather than being on their feet and continuously doing physical labor (Tractors Dekho, 2025). On the other hand, the implementation of technological monitoring systems has led to a great deal of "technostress" and "digital fatigue." There is also strong evidence to suggest that AI-influenced work demands lead to lower employee well-being, except when there is a strong and positive organizational response (Research Journal for Social Affairs, 2025). Ali and Jain (2025) conducted research on MNCs in Delhi-NCR; they found that AI made work tasks easier to perform for employees and less stressful overall but simultaneously led to increased anxiety for employees due to being constantly monitored and measurable at real time as well as the perceived decrease of worker autonomy (Scribd, 2025). In light of this and in accordance with the New Delhi Declaration on the Impact of Artificial Intelligence (2026), organizations are now being encouraged to adopt a human-centric approach (MANAV) to their AI role transition practices to make sure they keep the focus on human purpose and not only on a number of units produced (MeitY, 2026; IDC, 2026).

Socio-technical perspectives also note that technology does not impact society in a single way; rather, the impact of new technologies will vary depending on where and how they were created or used in society. Researchers from Science & Technology Studies support the idea of "human-centred" AI and its three main attributes: fairness, worker involvement, and ethical governance. Because employment plays a significant role in shaping personal identity and social status, changes in job roles or workplace monitoring can influence workers' sense of self and professional dignity (Scribd, 2025).

Technological advancements can also interact with gender dynamics. For example, the elimination of physical labour by machines will allow for the introduction of new job opportunities to women and men from all walks of society. Global surveys show that automatic systems take away the "dirty, dangerous, and boring" facets of job performance and allow for a larger variety of employment options for women and other minorities (World Economic Forum, 2019).

In addition, institutional and political structures/place have substantial effect on how technological change takes place. According to most economic research, periods of rapid technological advances also require investment in reskilling workers as well as in programs that provide social safety nets (Autor 2015). According to reports issued by ILO (2024) and NITI Aayog (2025) of India, the introduction of automating technologies will have an increasing impact on inequalities unless explicit efforts are made to provide support to those displaced II. In India alone, the global economic environment changes on a daily basis; therefore, the need for reskilling and supporting at-risk employees continues to grow.

Taken together, the framework guiding this study integrates four key perspectives:

1. Task-based labour economics, which explains how automation reshapes job structures and skill requirements;

2. Organisational psychology, which addresses the psychosocial consequences of technological change;
3. Gender and sociology of work look at how changes in technology affect the demographics of the workforce.
4. Policy analysis and institutional analysis point to how the work of government creates opportunities for inclusive outcomes.

Thus, the study incorporates these three perspectives to examine the transformation of the Indian labour market in relation to a broader interdisciplinary understanding of technology.

Methodology

This study employs a qualitative literature review combined with thematic analysis to examine the evolving relationship between AI technologies and labour transformation in India's agricultural and manufacturing sectors. The review focuses primarily on literature published between 2015 and 2026, a period characterised by rapid expansion in AI applications and increasing policy engagement with digital technologies in India.

Even though we were paying attention to current trends; we leaned heavily on traditional theoretical economic principles when trying to explain the relationship between machines and humans throughout history regarding division of labour. By thematically analysing all of these sources of evidence; we could go beyond statistics and gain insight into the changing skillset, psychological burden created by being monitored/observed, as well as how gender has changed in the current workplace in India.

The selected literature was analysed thematically. Particular attention was given to recurring patterns concerning:

- productivity effects associated with AI adoption,
- shifts in skills and task structures,
- psychosocial consequences for workers, and
- gender-related implications of technological change.

Several limitations should be noted. The analysis herein is based on secondary sources of information, that is, the scope of existing literature, but will therefore explore in-depth, specific aspects of the work experience of Indian workers, including many in India's rural areas and the informal sector. However, due to the decrease in the number of empirical studies documenting the work experiences of Indian workers, there is limited availability of systematic data that shows specific labour outcomes. Given the rapid pace of technological advancements, many recent programs have not been evaluated with long-term research. Despite these limitations, the combination of scholarly research, policy documents, and case studies provides a broad and current perspective to what AI is expected to do shape the future of Indian work practices.

Case Studies

For the agriculture sector an example can be found through the implementation of the Saagu Baagu program in Telangana which was launched from 2021 up to 2024 that provides AI-based advisory systems to help chilli farmers with managing their crop production; The system uses soil sensors, images that are recognisable by the machine and also provides chatbots via WhatsApp which are able to work in local languages for farmers to get proper recommendations on how to use fertilizers/pesticides/and manage their produce correctly. The productivity results for those using this technology showed great improvement across the board with farmers harvesting approximately 21% more chilli per acre but with a reduction of 9% for usage of pesticides and 5% for usage of fertilizers; The quality of their crops also improved resulting in an increase of 8% value for farmers in the market; Thus, demonstrating how locally relevant AI tools can greatly enhance the decision making capabilities for farmers and provide them more stability with their income. (Deep Learning.AI, 2024).

A second example within agriculture can be found with the Ag Robot pest management initiative which was trailed in Rajasthan specifically focusing on districts like Kota and Bundi; This Ag Robot system will provide farmers with robotically fitted spraying machines that are able to better distribute pesticides than traditional applications; Reportedly farmers using this system had a 30% reduction(output cost) when compared to traditional methods; This was achieved via the efficiency of pesticide and seed use; In addition to lower overall input costs these trials demonstrated that farmers outfitted with these tools were able to reduce pest damage by as much as 45%.

The impact of technological advances, such as robotics and ergonomic workstations, on gender composition in the workforce has been remarkably well documented by Mahindra Group's Swaraj Tractors manufacturing facility located in Punjab, India. In the last decade since the start of automation at this facility, there has been a significant increase in the number of women who are employed at the facility. The percentage of female employees rose from approximately 1.5 percent in 2013 to more than 10 percent by 2024 (Tractors Dekho, 2025).

There have been similar trends in other automotive manufacturing facilities in India. Companies such as Tata Motors and MG have made concerted efforts to employ women technicians in the automated assembly lines (IBEF, 2024). At MG's Halol facility, female employees represent approximately 34 percent of the workforce, demonstrating the need for redesigning industrial processes to increase female participant levels in roles that have traditionally been held exclusively by men.

The above examples illustrate how AI is beginning to transform labour practices across a wide diversity of economic situations in India. Each sector employs its own unique technology; however, the resulting changes in disbursed productivity, task organisation and workers are consistent across all sectors.

Comparative Synthesis

An analysis of AI usage around the world shows similarities and differences across these industries. AI technology has provided increased productivity across farming and manufacturing; with farm production improving due to increased crop yields, more efficient use of resources, and improved access to farming information; while industrial output has generally also been increased through the use of automated machinery, improved quality control and more efficient use of time in operations.

Although both industries use technology to improve how we work, the impact and conversion of skills will be very different because of the differences in agriculture and manufacturing. Therefore, we will explore some specific examples to illustrate this relationship; for example, innovations such as simulation modelling techniques and remote sensing methods are enabling a transformation in agriculture from a more traditional method of farming to one that is driven by data (i.e., 'agro-science'). In particular, the work done by Agarwal, Kalra, Chander and Pathak (2006) on the "Info Crop" simulation model, which is a dynamic simulation-based tool for modelling the productivity of crops used in tropical agro-ecosystems and assessing the effects of climatic variability and pest pressure on crop yields, represents one of the early overall transformations to enable forecasting of crop yields using modern science and measuring the environmental impact on crops. Building upon this analytical capacity, Bhatt et al. (2021) highlighted how the use of remote sensing technologies (i.e. satellites) have enabled real-time monitoring of crop health throughout India and, therefore, enabled timely and appropriate application of crop management practices that were previously not feasible due to lack of information. Another means through which digital tools are being used to provide farmers with crop management data is by using aerial technology (e.g. drones) that are now being deployed throughout India (Chandel et al., 2021). As noted by Chandel et al. (2021), drone technology is no longer viewed as a novelty in Indian Agriculture; it has become a standard component of the modernisation of field operations and increasing agricultural productivity. Consequently, such digital tools require farmer interaction with a digital advisory system; therefore, the skill set required to use these digital tools includes a basic level of data interpretation and computer literacy (Shanu & Lakshminarayana, 2025).

In terms of manufacturing, the transition to automation means more than just a technological upgrade; it is a complete reconstruction of both industry capacity and employees' occupations. Robotics and automated systems are also changing how global industries will develop in the future by maximizing efficiency and productivity in the manufacturing process (Agarwal, 2023). One area where this can be seen is in India's automobile industry, where Agarwal et al. (2024) used Analytic Hierarchy Process (AHP) modelling to determine and rank the obstacles to the implementation of “green” smart manufacturing as a part of the Industry 4.0 paradigm. This transition is ultimately very dependent on software, where Ajiga, Okeleke, Folorunsho & Ezeigweneme (2024) emphasized the role of automation using software to enhance overall operational efficiency and Alavian, Eun, Meerkov & Zhang (2019) noted that advanced "smart production systems" can now automate the intricate decision-making processes that used to be carried out by human managers.

The new technologies do more than improve production efficiency; they also allow for new possibilities in terms of what can be done in the manufacturing process (e.g., concrete 3D printing) (Akkoyun & Günal, 2025) and using a Novel Robotic Arm to perform precise tasks (like micro-friction stir welding) (Alghloom & Ay, 2022). That noted, all authors agree with Andersson (2011) regarding the potential for human-automation challenges and the importance of properly managing the worker-machine relationship as part of those challenges. In some instances, such as in the automobile sector, the use of robotic automation has had an incredible positive impact on production efficiency (i.e., Ashmitha & Arumugasamy, 2024) and production efficiencies are consistent across global value chains (e.g., automotive, wiring harness-including) (Azmeh, Nguyen & Kuhn, 2022). Finally, Bai (2024) concludes that new robotic technologies have changed the factory floor and have also fundamentally changed the nature of society in relation to work and industrialization.

The psychosocial implications of AI adoption also vary. For farmers, AI tools are often perceived primarily as decision-support systems that help manage environmental and market uncertainties (DeepLearning.AI, 2024; Press Information Bureau [PIB], 2026). Within industrial settings, however, the integration of AI-based monitoring technologies has generated concerns regarding workplace surveillance and job security (Scribd, 2025). Brougham and Haar's (2018) article suggest that how employees perceive and feel about

STARA (Smart Technology, Artificial Intelligence, Robotics, and Algorithms) affects their current job performance and engagement levels. Brynjolfsson and McAfee (2014) describe our current experience with STARA as the Second Machine Age where advanced technological capabilities can generate success; however, we are starting to reconsider what it means to create value as humans. Unfortunately, this can have repercussions, including experiencing "techno-stress" (Borle et al., 2021) due to continuous use of these tools that will negatively impact our mental health unless they are balanced with strong support systems (Rao, S. U. M., & Supriya, E., 2025).

As more jobs are threatened and likely to be replaced by computer/process technological advancements (Frey & Osborne, 2017), the ability to adapt to these job-related changes has also become a critical skill. According to Judge et al. (1999), ways people naturally cope with changes play a large role in helping them transition through such changes without experiencing burnout or stress. In our review, the only way to sustain long-lasting change is through a human-first approach. The International Labour Organization (2021) contends that human beings must be placed ahead of technology in all work plans According to Winsor and Paik (2024), enabling the multifaceted abilities of humanity is the most effective method for working through the most significant global challenges. Our perception of time, our location in time, and how we view ourselves throughout time all impact our ability to adjust to life-altering events. Our plans and aspirations for the future are also determined by our perception and assessment of how much time we have. Carstensen (2006) states that our assessment of our time and our perception of how much time has passed plays a critical role in shaping our plans and aspirations for the future.

Gender issues present another area where we can see differences. Digital technologies have provided increased access to agricultural information for many women but they still experience barriers, like limited access to land ownership, that prevent them from participating fully in decisions about farming. In the manufacturing sector we have also seen significant changes with the introduction of automation and robotics. Many physical demands have been removed from specific work-related jobs, which has opened up the shop floor for women to work and increase their presence in this sector (Tractors Dekho, 2025; India Brand Equity Foundation [IBEF], 2024).

The various approaches of the agriculture and the manufacturing sectors are represented through their policies. While agriculture is trying to build a modern digital extension service system and improve precision at farm level (for example, the Digital Agriculture Mission initiatives as per PIB 2026), the focus of the Manufacturing Sector is primarily on modernising their factories, providing automation incentives and government-funded up-skilling programs to assist workers (ILO, 2024).

Discussion

The findings presented here highlight several implications for understanding technological change and labor transformations happening within India today. Our research shows that integrating AI and robotics into India's labor force does not simply mean replacing jobs but is also complicated by new work structures. As for agriculture, the replacement will be mostly augmentative, with the use of things such as remote sensing technology and the InfoCrop model to help farmers with their decision making in an unstable environment (Aggarwal et al., 2006; Bhatt et al., 2021). This is consistent with a "task-based approach" to technology, where technology takes care of data processing and the human farmer is still in charge of making decisions regarding all data, (Autor et al., 2003). However, these psychological "buffers" provided by technology to help farmers cope effectively have no use unless the technology is available to all farmers. The "technological capital" gap must also be closed; for example, women that do not have any land ownership rights will not feel the benefits of using digital technology in agriculture (Sharma et al., 2022).

Unlike the manufacturing sector, which is becoming increasingly reliant on algorithmic management/monitoring systems alongside use of robotics in places like Swaraj Tractors; consequently making it possible for all employees including women to work at the same time (because no longer any physical barriers); however at the same time has created 'technostress' due to how workers now have less control over their own environment through real-time performance data being tracked by these types of systems (because they don’t have as much input/feedback from supervisors/employers); therefore in order for India to achieve the MANAV (human centric) vision outlined within the New Delhi Declaration 2026; it will be necessary for companies to no longer focus strictly on technical capabilities/effectiveness but also develop ways in which to enhance employee's psychological health/overall quality of life while at work by providing greater levels of “digital dignity” than currently offered (Mahatma Gandhi–i.e. Not just from physicality but emotionally also.), MeitY 2026).

The transition to the Second Machine Age in India will call for a policy framework that is concerned both with productivity and social protection. As functions shift to human-AI collaboration (IDC, 2026), the focus should be on developing reskilling initiatives that consider workers to be creative collaborators within a socio-technical framework, rather than simply a unit capable of being replaced. Indicators of the success of the Fourth Industrial Revolution in India will include not only the projected growth rate of 21% in yield increases from agriculture or the increase in female participation on the shop floor, but also the ability of the workforce to successfully adapt to these changes without experiencing systemic burnout or the loss of their professional identity (Rao & Supriya, 2025; Judge et al., 1999).

Conclusion

Bringing AI into India's farms and factories is a double-edged sword that forces us to look beyond just profit and yield. It's clear that we need to start measuring success by how these tools actually affect the people using them. On one hand, data-driven systems and smart robots have clearly made a huge difference by boosting harvests and opening up factory jobs for women that were previously too physically demanding. The use of technology has created new 'stressors' within the workplace for example, feeling as if you are being constantly monitored by your employer and worrying that a machine will take away autonomy of employment. As India continues to transition into the machine age, the most significant issue will be continuing technological advancement without potentially sacrificing mental or social collateral. Future research on worker experiences, particularly to better represent the rural and informal sectors of the workforce not represented in existing literature, should start with primary empirical data collection. Longitudinal studies researching how workers are impacted by AI implementation in regards to their employment status, income distribution, and general well-being would provide insight into how to build a comprehensive understanding of worker dynamics occurring as India transitions to using more advanced technologies.

The issue that India today, is not merely how workers can transit into using advanced technologies; rather, a critical component of that process will include the creating institutions and social constructs that will ensure all of those technologies promote and advance the employee's overall experience of inclusion and enhance their progress toward meeting their potential as a productive human being.

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