



Impact of Automation on Workers in Informal Industrial Work in North India

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Abstract

Automation is transforming the manufacturing sector across the world. However the research on its effects on workers is insufficient, particularly in the developing economies. In this regard, this study focuses on automation awareness, perceptions of job insecurity, skills transformation, and well-being of workers amongst 67 shop floor workers working at an automobile parts manufacturing firm in Jaipur, India. The survey was conducted in Hindi language with a physical questionnaire amongst the workers in April 2026 focusing on twelve dimensions of automation such as awareness about automation, benefits and limitations, training needs, willingness to invest in skills development, and preferred adaptation methods in case of job displacement. This study found workers aware of automation but confused about what it entails with most of the respondents having a narrow view of automation as machines replacing tasks rather than as digital transformation of industrial processes. Moreover, the workers were concerned about productivity aspects of automation on one hand and fear of losing their jobs, income disparity, and inability to afford the training costs on the other. There was not a single worker who thought that their skills would be adequate enough for an automated environment. Taking into account recent research on automation and its impact on worker well-being (Nazareno & Schiff, 2021; Li et al., 2026), the analysis shows that the above perceptions have practical implications for the well-being of workers, and, therefore, the policies aimed at tackling the consequences of automation should pay due attention to these problems. The results of this paper highlights the importance of targeted training programs, well-funded retraining opportunities so that they could be affordable for the masses and a stronger social safety net protection in order to account for the human side of industrial automation. In accordance with Kasy and Sautmann (2022), the optimal approach to solving problems related to automation should be context-specific, and the current research provides a solid basis for that.

Keywords: Automation; Technology; Informal Work; Industrial Corridors

1. Introduction

Industries everywhere are witnessing a radical shift as more and more machines replace human effort through automation. Where such economies like India manufacturing sector alone employs approximately 14.4 million registered factory workers, with the organised sector accounting for over 6.5 million of those, and the majority operating without formal social protection or retraining entitlements (MoSPI, 2022). For these workers, the need to understand and adapt to the impacts of automation is not a distant concern but an immediate one. While much literature regarding automation is concerned with big picture questions regarding predicted job losses, sector vulnerability, net impact on employment on a decade time frame, etc., there is very little said about how automation is perceived and reacted to by workers themselves.

This paper investigates how the laborers at an automobile parts plant in Jaipur, India, perceive automation and threats associated with it to their jobs, and how they envision reacting to it so that the threat doesn't come true. Another important aspect this paper will consider is how automation affects workers emotionally – the insecurity, upskilling pressure, and displacement anxiety of those who are going through it.

Such research would be especially relevant in light of India's manufacturing industry. It is the country's one of the largest sectors in terms of employment and according to the Periodic Labour Force Survey 2022-23, the majority of the organised manufacturing workers belong to the 20-40 age group and just have secondary level

education only. This specific population segment is precisely the one that tends to be the first to encounter job elimination due to automation (Ministry of Statistics and Programme Implementation [MoSPI], 2023). There are about 14 million workers employed in the factories in the organised manufacturing sector of India (MoSPI, 2022), whereas McKinsey Global Institute considers 50-70% of manufacturing tasks are automatable in accordance with the technologies currently used (MGI, 2017; 2022).

This study will analyse structured surveys conducted among 67 employees of an automobile parts factory in Jaipur in April 2026. The questionnaire consisted of 12 questions, was originally designed in English but translated into Hindi.

Organization of this paper: Section 2 reviews the study in light of the literature on automation, labour changes, skill formation, and well-being; Section 3 outlines and analyzes survey results along the main dimensions; Section 4 examines these results in the context of the larger literature; and Section 5 concludes with policy conclusions and suggestions for future research.

2. Literature Review

The present research is set within the context of three major research areas currently being explored: the impact of automation on the labour market; the difficulties faced by workers in terms of skilling and workforce readiness; and finally the lesser-known impact of automation on the well-being of workers. Firstly, Acemoglu and Restrepo (2019) provide an interesting framework to consider the issue of labour markets, differentiating between automation that substitutes labour and that which complements labour. This duality appears in many following papers. Bessen et al. (2022), on the basis of their analysis of Dutch firm-level data show how automation increases efficiency but also leads to higher rates of labour turnover and loss of income, especially for the old and medium-educated people..

According to Bonnefon et al. (2019) people who have witnessed automation in action, the anxiety level about automation is significantly higher among those workers. The World Bank (2019) and OECD (2021) point out that secondary-educated manufacturing workers face a unique vulnerability: skilled enough to avoid substitution, yet without necessary digital skills to transition easily. The WEF Future of Jobs Report (2023) estimates 44% of core skills will be disrupted by 2027, however, to varying degrees depending on skill level. Cramarenco et al. (2023) suggest upskilling has become a norm in reaction to technological disruption, yet Hanushek et al. (2022) argue such norms have failed to be accompanied by accessible and affordable institutional arrangements, particularly in the case of developing countries. Toker (2023) stresses the need for learning paths created by employers, whereas Boeren (2020) identifies perception of employment insecurity as an obstacle to training participation.

Automations and well-being literature, although not entirely established yet, is directly pertinent to the topic. Nazareno and Schiff (2021) prove the negative impact of automation risk on employee well-being and health. Giuntella et al. (2023) confirm decline in life satisfaction experienced by workers exposed to automation. AI. Ruiz-Vanoye et al. (2025) aim to develop a theoretical approach towards the well-being consequences of AI use through the "happiness pyramid". Li et al. (2026) prove the negative impact of automations on well-being is the strongest among the vulnerable groups, which includes low-educated workers – dominant demographic in this study sample.

The body of literature reviewed above provides an entry point into studying awareness of automation, perceptions of risk associated with automation, preparedness for skills transformation, and well-being of Indian manufacturing workers. This study hopes to provide an empirical foundation for policies that respond to both economic disruptions caused by automation and its negative impacts on people.

3. Research Objective

The main purpose of this study is to understand how industrial workers perceive and respond to automation, with special attention paid to implications for the well-being of workers and their skills transformation.

Specific objectives are:

1. To assess awareness and understanding of automation among shop-floor workers employed at a parts manufacturing plant in Jaipur, India.
2. To examine perceptions of job security and automation risk among these workers.
3. To measure attitudes to reskilling and readiness to undertake relevant training.
4. To contextualise findings from the primary research using existing literature on automation, labour market changes, and worker well-being in manufacturing.
5. To draw policy implications for helping workers adapt to technology changes in industry.

4. Methodology and Data Collection

4.1 Research Design

In this study, primary data was collected from industrial workers through a structured survey questionnaire in Jaipur, where a quantitative approach was chosen to identify patterns across a group of people. Through the survey, we also got to know what workers understand about automation, if they see automation as a companion for them or they feel threatened by it. We were able to conduct the survey among a large group of people rather than relying on individual accounts.

4.2 The Questionnaire

The questionnaire for this study is attached in the appendix. This questionnaire has 12 questions that go around four sections: The first section asks about the basic background information of that worker, mainly their age, gender, what education they have completed, years of experience in this job sector. The second section looks and tries to understand how workers see automation. The third section asks if the workers feel the need to train themselves and if the workers are willing to spend in order to upskill themselves. The last section, the fourth section, explores if the workers feel secure in their jobs and what would their action be if their work becomes redundant due to automation.

All questions are multiple-choice questions, and some of them allow the respondent to select up to three answers in the questions that are about the advantages or disadvantages of automation. This questionnaire was designed in a way to pick up three options because there are certain questions where workers rarely hold a single view. Keeping in mind that the respondents are shop floor workers rather than professionals, we kept the language of the questionnaire really simple and direct so that they are able to understand things easily.

4.3 Participants and Setting

This survey took place in an automobile parts manufacturing factory in Jaipur, Rajasthan. The factory produces components for the automobile industry and is a medium-scale manufacturing unit.

In this survey, 67 workers participated in total. These workers were drawn from the factory floor in roles such as quality checking, material handling, CNC operation, construction work, and assembly. Workers were informed beforehand that the survey was for academic research and that their responses were anonymous. They were also informed that none of their information would be shared with the employer. The only personal information collected from them was their name, which was used to track responses during data entry and was not included in any part of the survey's analysis.

4.4 How the Data Was Collected

This survey was conducted in April 2026. Printed questionnaire forms were distributed to workers by the researcher during breaks in the production schedule. This was done so as not to interfere with their work or hamper the factory's production. Workers filled in the forms themselves, and where a question was unclear, the researcher explained what was being asked without influencing the respondent's choice of any particular option.

As the primary language spoken by the workers at the facility is Hindi, the questionnaire was originally prepared in English and then translated into Hindi before distribution. This was done to ensure respondents could engage fully with each question rather than being constrained by language barriers. Responses collected in Hindi were then translated back into English by the researcher to allow for proper analysis of the data.

Paper forms were used instead of an online survey for a straightforward reason: many of the workers in the factory do not own smartphones. By distributing physical forms, the researcher ensured that no respondent was excluded due to lack of digital access.

5. Demographic Profile of the Sample

5.1 Age Distribution

The age composition of the survey reflects a predominantly youthful workforce in India's industrial sector. As shown in Figure 1, the dominant cohort is the 20–29 years age group, comprising 31 respondents (38%), followed by the 30–39 years age group, accounting for 26 respondents (32%). The 40–49 years age group comes next, with 17 respondents (20.7%). The 50–59 years age group follows, representing 7 respondents (8.5%). The survey also included a single participant under the age of 20.

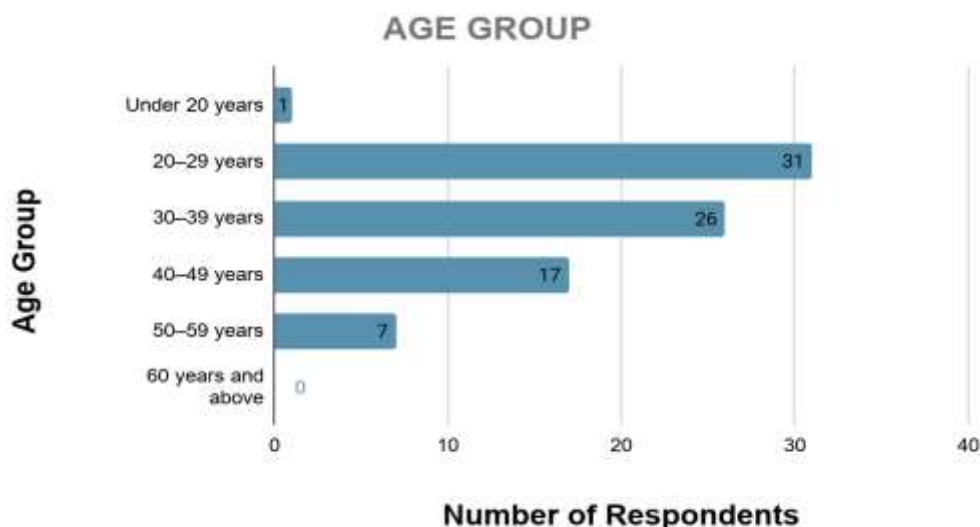


Figure 1: Age Distribution of Survey Respondents (N=67). The 20–29 years cohort constitutes the largest segment, reflecting the young demographic profile of the Indian manufacturing workforce

The cohort aged between 20 and 39 years accounts for 70% of the sample. This shows that younger workers form a large share of the manufacturing sector's workforce. The same finding is seen in the Periodic Labour Force Survey (PLFS) 2022-23, which has consistently shown that the majority of India's organised manufacturing workforce falls within the 20-45 age bracket (Ministry of Statistics and Programme Implementation, 2023).

Only a small proportion of workers in the sample are above the age of 50, a pattern also reflected in the findings of the International Labour Organization (ILO). The ILO suggests that manufacturing workers aged above 50 are more likely to be affected by displacement due to automation. It also suggests that this age group is the least likely to participate in employer-sponsored re-training programs (ILO, 2019). Viewed from an automation readiness perspective, the higher concentration of younger workers in the sample presents both opportunities and challenges. Younger employees, having grown up in an increasingly digital environment, tend to be more adept at new technologies. However, their limited work experience and lower levels of capital accumulation make them more vulnerable to wage pressures and job displacement during periods of industrial transformation (McKinsey Global Institute, 2022).

5.2 Gender Composition (Q2)

As shown in Figure 2, male respondents account for 87% of participants (87.8%), with women comprising the remaining 12.2%. No respondent selected non-binary or "prefer not to say."

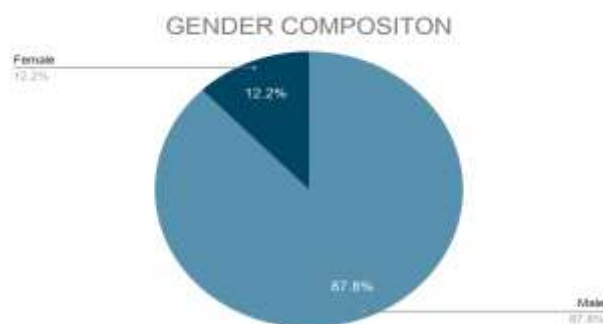


Figure 2: Gender Composition of Survey Respondents (N=67). The 87.8% male dominance mirrors the structural gender composition of India's organised manufacturing sector, as reported in ASI and PLFS datasets.

As shown in Figure 2, male respondents account for 72 participants (87.8%), while women comprise the remaining 10 participants (12.2%). No respondent selected "non-binary" or "prefer not to say" as their option.

According to the Annual Survey of Industries (2021–22), male workers account for 78–88% of the workforce across heavy manufacturing sub-sectors such as basic metals, fabricated metal products, and engineering goods, with some segments exceeding 90%. The PLFS 2022–23 links constant low female participation in formal

manufacturing to a familiar cluster of barriers, including poor transport access, absence of crèche facilities, night-shift restrictions under factory legislation, and occupational channelling that pushes women toward garments and food processing rather than capital-intensive production (MoSPI, 2022; 2023). ASI-tracked enterprises employ women at roughly 16-19% of the total factory workforce at the national level, showing that the current sample's 12.2% is at the lower end of that range (ILO, 2022; NFHS-5, 2021).

This pattern is further illustrated by data on workforce status by gender, which shows that 78% of male graduates are workers, while only 33% of female graduates hold worker status, with 59% of female graduates outside the labour workforce entirely (PLFS, 2024).

The implications for automation research are significant. Brussevich et al. (2018) and McKinsey Global Institute (2019) both found that women are disproportionately concentrated in routine work, exactly the kind most exposed to automation. Although the female cohort in this study is too small for subgroup analysis, their responses align with the wider evidence. This underscores the need for a follow-up study using gender-stratified sampling to properly examine this dimension in the Indian industrial context.

5.3 Educational Attainment (Q3)

As represented in Figure 3, 63 respondents (76.8%) hold secondary school qualifications. 19 of them (23.2%) have a diploma, vocational certificate, or ITI, and no one in the sample holds a degree or postgraduate qualification.

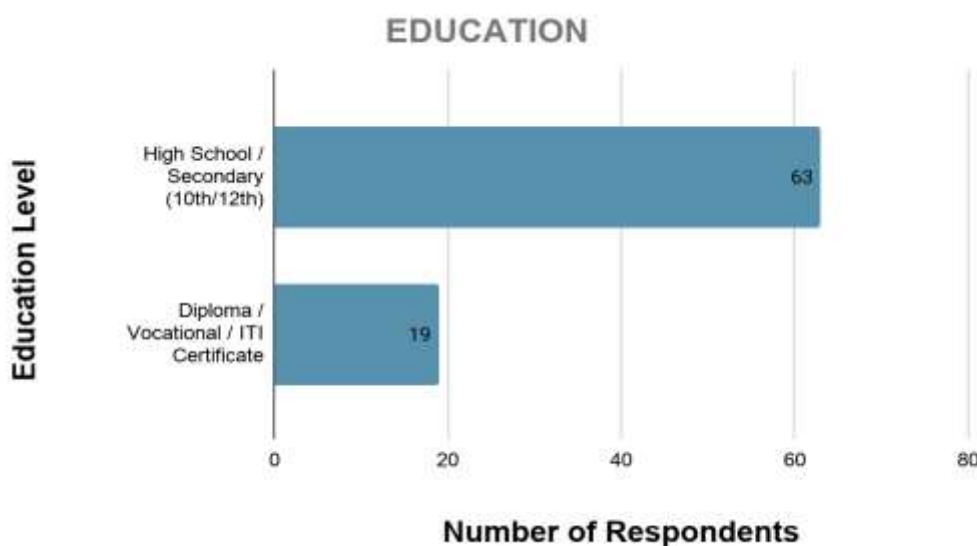


Figure 3: Educational Attainment of Survey Respondents (N=67). Secondary school completion dominates at 76.8%, while 23.2% hold vocational/ITI qualifications — a distribution consistent with India's industrial workforce educational profile.

The distribution closely mirrors the national pattern. The PLFS 2022-23 places ITI and vocational qualification holders at 18-22% of shop floor roles, with secondary-school completion accounting for the largest share, at 65-72% (MoSPI, 2023).

The mismatch between educational supply and labour market demand is not confined to vocational workers. As the State of Working India 2026 documents, graduate employment has failed to keep pace with graduate supply since 2011, with real wages for male graduates falling outright over the same period (Azim Premji University, 2026).

The ITI cohort's qualifications are built around trade competencies: mechanical fitting, basic electrical work, and operational maintenance. Their design remains largely unchanged from a generation ago. They do not, as a rule, cover PLCs, SCADA systems, industrial IoT, or data-driven quality management. The NSDC has acknowledged this gap repeatedly in its Sector Skill Council reports, noting that ITI curricula have not kept pace with what smart manufacturing now demands (NSDC, 2022).

Both the World Bank (2019) and OECD (2021) describe a similar broader picture: secondary-educated workers occupy a highly exposed position in the automation transition. These workers are not unskilled — they carry years of operational knowledge — but even with their qualifications, they are not equipped to move into the digital roles

automation is creating. They occupy a congested middle ground: too experienced to be easily displaced, yet underqualified to adapt to the transition without serious reskilling investment.

5.4 Work Experience (Q4)



Figure 4 shows a fairly even distribution of the workforce across experience bands. The 4-7-year bracket is the largest, with 20 respondents (24.4%), followed by the 1-3 year bracket with 19 respondents (23.2%). The 8-12 year bracket accounts for 15 respondents (18.3%). Workers with less than one year of experience number 11 (13.4%), while only 5 workers (6.1%) have more than two decades of experience. In total, more than 60% of the sample falls within the 1 to 12 year experience bracket. This reflects the young age profile established earlier and aligns with PLFS data placing median shop floor experience in registered manufacturing between 5 and 9 years (MoSPI, 2023).

Figure 4: Years of Professional Work Experience (N=67). The concentration in the 1–12 years range reflects relatively recent workforce entry, consistent with the youthful age distribution.

This data shows that automation readiness is not straightforward. Younger workers are more willing to adjust to technological changes in the industry and are more inquisitive about learning new systems. At the same time, they still lack the operational instincts and situational knowledge that experienced workers rely on to make sense of disruptions when they occur. The small cohort with 20+ years on the floor brings exactly the depth needed, but their share of just 6.1% shows that workers with this level of accumulated industrial experience have become increasingly rare.

5.5 Sector Distribution (Q5)

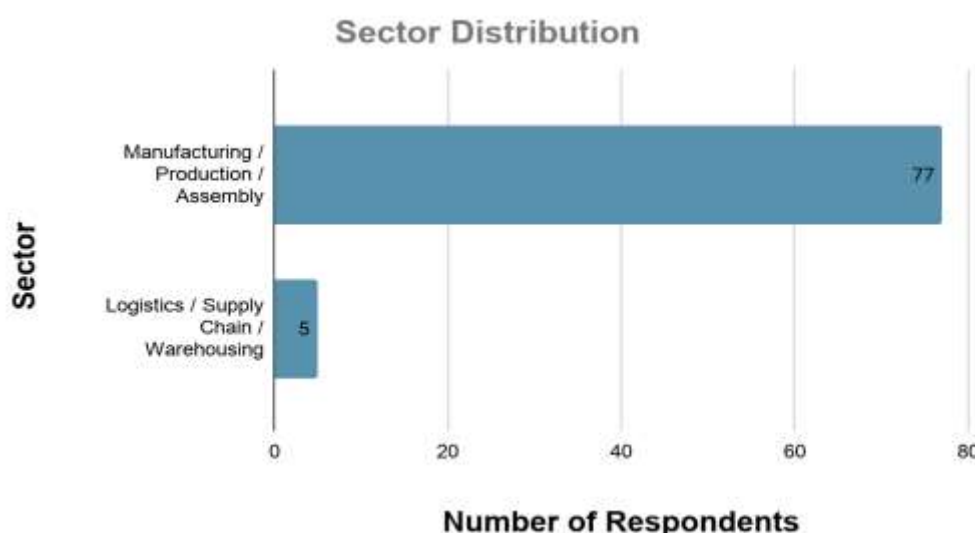


Figure 5 shows 93.9% of respondents i.e. 77 respondents working in the manufacturing sector, particularly in production and assembly, with the remaining 5 respondents (6.1%) involved in logistics, supply chain, and warehousing. No other sectors are represented.

Figure 5: Sector Distribution of Respondents (N=67). Manufacturing dominates at 93.9%, providing a focused lens on automation dynamics in India's core industrial workforce.

Such a concentration is by intention rather than by incident. Manufacturing is the sector where the pressure of automation is most visible, and it is also one of India's largest sources of formal employment (MoSPI, 2022; Ministry of Labour and Employment, 2022). The 2020-21 records from ASI showed approximately 14.4 million factory workers nationally in India, of whom over 6.5 million are in the organized sector (MoSPI, 2022). McKinsey Global Institute also estimated that between 50% and 70% of activities in labour-intensive and manufacturing sectors have a high probability of automation using technologies that either already exist or could be deployed in the near future (MGI, 2017; 2022).

Focusing on this sector allowed the study to concentrate on stakeholders where this concentration is high. The concerns and perceptions discussed in the following sections are rooted largely in real technological changes happening today, not in the distant future. They come from people whose working lives are already being shaped by automation.

5.6 Awareness and Understanding of Automation (Q6)

In the appendix, where question 6 talks about how the worker would describe automation in the context of their workplace, respondents picked a single description of automation that best suited their understanding. They were provided with 6 options, including an explicit response that said, "I am not sure." As illustrated by Figure 6, all 67 answers: we just have three options and no admitting uncertainty.

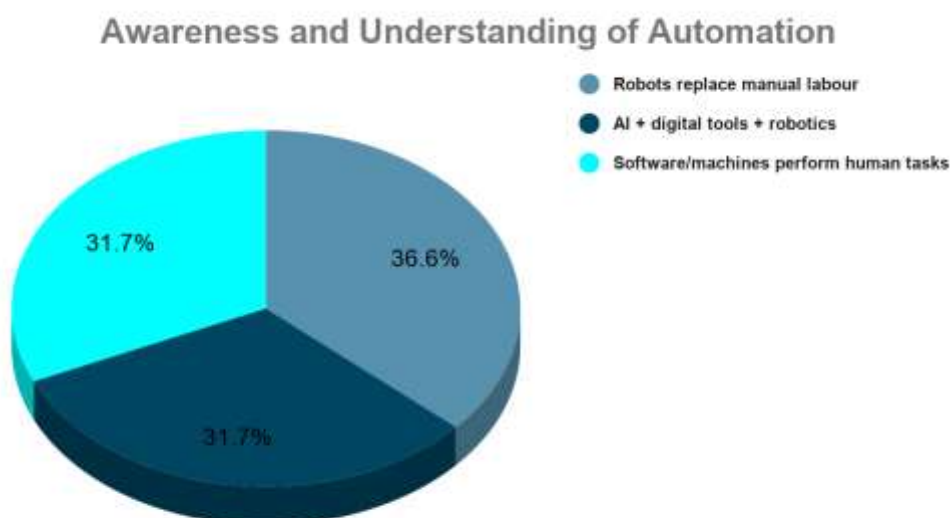


Figure 6: Workers' Self-Reported Understanding of Automation (N=67). The three-way near-equal distribution across narrow, broad, and integrated conceptualisations indicates fragmented yet substantive awareness.

The largest number of respondents, 30 (36.6%), chose the option of robots replacing manual labor. This is consistent with what is typically observed among workers in such setups: conveyor systems and robotic machinery naturally define automation by what they can see. This tendency was also reported by Frey and Osborne (2013) among industrial workers. Of the remaining 52 respondents, the split was even, with 26 (31.7%) choosing a broader software and machine substitution definition, and the remaining 26 (31.7%) choosing the comprehensive framing option, describing automation as a combination of digital tools, AI, and robotics working together.

One thing worth pausing on is that there were zero responses for "unsure." Rather than showing universal awareness, this more likely reflects a reluctance to admit uncertainty in a face-to-face survey setting (Podsakoff et al., 2003). Workers, though largely unaware of the algorithmic and data-driven dimensions that operate less visibly behind the machinery, were still confident about what they had been directly observing.

That distinction carries real consequences. Acemoglu and Restrepo (2019) separate automation that displaces workers from automation that augments them, and the dominance of the displacement framing here suggests most respondents see the technology as something being done to them. Brynjolfsson and McAfee (2014) warn that this outlook tends to suppress the upskilling investment that would actually reduce vulnerability. The NSDC has begun incorporating digital awareness into some training frameworks, but this data suggests conceptual understanding on the shop floor remains observation-driven rather than systematically built.

5.7 Perceived Need for Training (Q7)

As illustrated in Figure 9, 40 respondents (48.8%) strongly feel the need for training, with 22 (26.8%) seeing the need for basic introductory training as sufficient and 20 (24.4%) being uncertain about whether they need the skills. Out of those 80 respondents, not a single respondent selected either of the two negative options, and none of them also talked about their skills being adequate. Nobody mentioned automation being irrelevant to their work



Figure 7: Self-Perceived Need for Automation-Related Training (N=67). A striking 75.6% of respondents expressed a definitive training need, with zero respondents indicating their current skills are sufficient.

The headline finding here is that workers strongly agreed on this view. They already sense that there is a problem, and this is not something they have to be told about, even though many of them could not name what they need to learn. The NSDC's 2022-23 Annual Report puts a number to this picture, projecting a skill gap of approximately 103 million workers across the manufacturing and related sectors by 2026, with the sharpest shortfall expected in digital manufacturing and automation-related competencies (NSDC, 2023).

The 24.4% expressing uncertainty deserves attention as a distinct group rather than a footnote. These are not workers who feel unthreatened. They feel the pressure but cannot yet see a clear path forward, which the ILO (2020) identifies as its own barrier to training participation. Workers who cannot identify what they need to learn are unlikely to go looking for it.

What's worth noting is the split between workers who want serious training and those who only seek a basic introduction. The second group is not unambitious; they are being realistic about what is required at this stage. Rather than pursuing deep technical mastery, what they need is enough clarity about the work to operate confidently across an automated plant. This distinction matters for how training is designed: a single programme pitched at one level will fail half the room. The WEF Future of Jobs Report (2023) projects that 44% of workers' core skills will be disrupted by 2027, and that disruption will not affect everyone in the same way or at the same depth.

5.8 Perceived Automation Risk to Current Role (Q8)

As shown in Figure 11, risk perception split almost perfectly three ways: 28 respondents (34.1%) assessed Low Risk, 27 (32.9%) Moderate Risk, and 27 (32.9%) Very High Risk. Nobody selected "No Risk" and nobody said they were uncertain. Every respondent had a view.

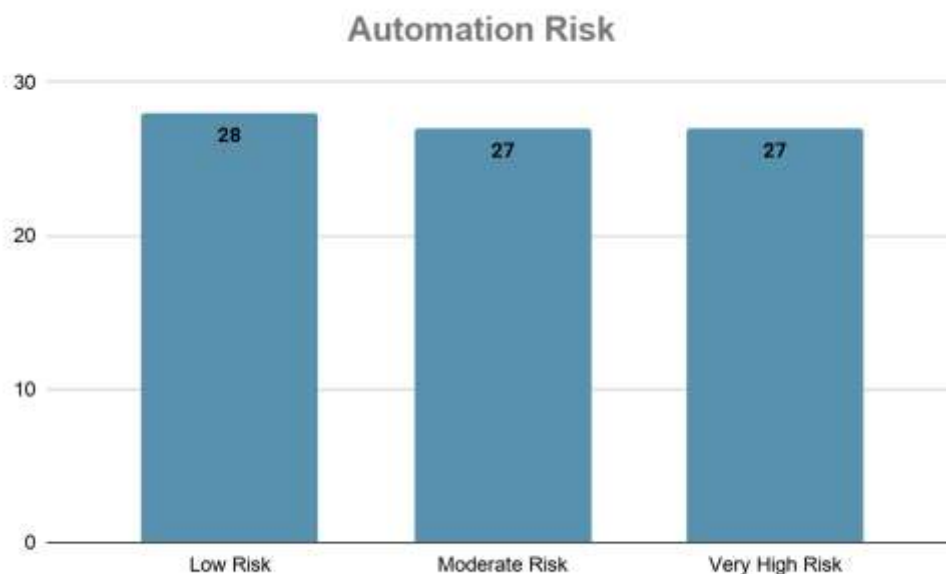


Figure 8: Perceived Automation Risk to Current Job or Industry (N=67). The near-equal three-way distribution across Low, Moderate, and Very High risk categories reflects significant inter-worker variation in automation threat perception within homogeneous occupational contexts.

That disagreement is an interesting finding. These are workers in the same sector, with similar educational backgrounds, doing broadly comparable work. Yet a third of them feel largely unthreatened while another third consider their jobs directly at risk. The gap cannot be explained by occupation alone. Tversky and Kahneman (1974) would point to availability heuristics: workers who have watched colleagues displaced or seen new machinery arrive on their specific line will naturally perceive the threat as more immediate than those who have not. Automation is not rolling out evenly across firms or production lines, and that unevenness produces genuinely different lived experiences within what looks, from the outside, like a uniform workforce.

The Very High Risk group warrants particular attention. Their responses across Q7 and Q8 suggest a coherent and consistent worldview: they were among those most likely to identify job loss and wage inequality as automation's primary consequences. The ILO (2019) describes this cluster as "automation-anxious" workers — people who understand what the technology can do and are not reassured by it. They are also the group most likely to benefit from concrete policy responses: retraining guarantees, income protection, and honest employer communication about technology adoption timelines.

The Low Risk group is harder to read. Some may genuinely occupy roles with enough complexity, human interaction, or task variety to be relatively resistant to substitution, the kind of work Brynjolfsson and Mitchell (2017) identify as automation-resistant. Others may simply be underestimating a real threat. Distinguishing between justified confidence and optimism bias is not something a survey instrument can resolve, and it points to a gap that follow-up qualitative research could usefully address.

McKinsey Global Institute (2022) estimates that 18 to 20 percent of India's manufacturing workforce will face significant task disruption by 2030, with a further 15 percent experiencing partial substitution. The WEF (2023) projects 85 million jobs displaced globally against 97 million created, with the distribution of those gains and losses falling very unevenly across skill levels. The three-way split in this sample reflects, in miniature, exactly that unevenness.

5.9 Preferred Course of Action if Job Becomes Automated (Q9)

As shown in Figure 12, responses spread across four options with no clear consensus. The most common choice was seeking a similar job elsewhere at the same pay, selected by 25 respondents (30.5%), followed closely by accepting any available work even at lower pay (24 respondents, 29.3%), actively upskilling within the same organisation (23 respondents, 28.0%), and starting a business or going freelance (10 respondents, 12.2%). Nobody chose higher education or early retirement.

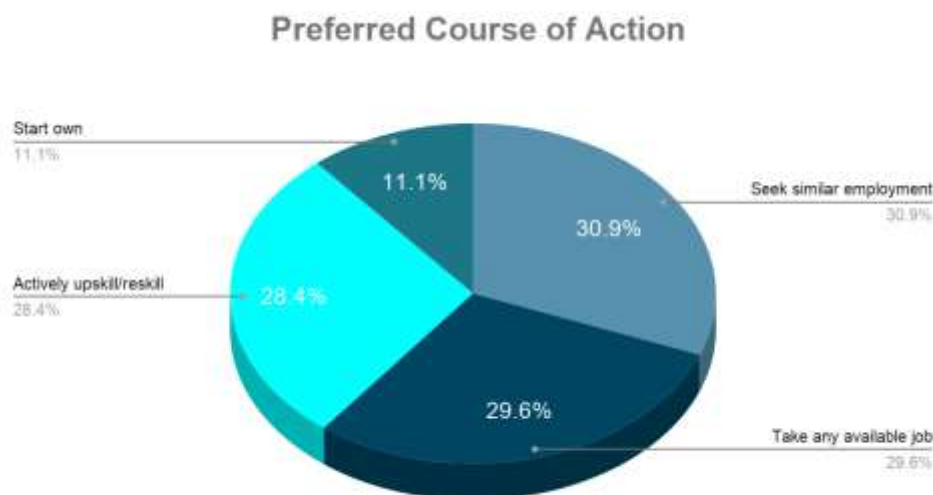


Figure 9: Preferred Course of Action if Job Becomes Automated (N=67). The distribution across four responses reveals a workforce divided between job-seeking mobility, proactive reskilling, and pragmatic downward employment flexibility.

The near-equal three-way split at the top is itself a finding. A workforce this divided on what it would do if displaced is a workforce that has not found a convincing answer. Each of the three dominant responses carries its own logic and its own limitations.

Seeking equivalent work elsewhere is a reasonable individual strategy, but it rests on an assumption that equivalent work exists somewhere. Acemoglu and Restrepo (2019) note that this assumption becomes increasingly fragile as automation spreads across entire industries rather than individual firms. Workers displaced from one plant may find that the same pressures have already arrived at the next one.

Accepting lower-paid work to stay employed is the most candid response in the set. It reflects a clear-eyed reading of limited options: few transferable skills, no meaningful social safety net, and a service sector that cannot absorb displaced manufacturing workers at comparable wages. The ILO (2018) describes this kind of labour market downgrading as one of the more economically damaging consequences of technology-driven displacement, particularly in middle-income countries, because it compounds inequality rather than simply redistributing work.

The 28.0% who would pursue upskilling within their current organisation are perhaps the most optimistic group, and not without reason. Their response implies a belief that their employer will invest in their transition rather than simply replace them. The OECD (2021) notes that internal upskilling works best when employers provide structured pathways, mentoring, and protected time for learning, conditions that are not standard in most Indian SME manufacturing settings. That workers are willing nonetheless is a signal worth acting on.

The 12.2% considering self-employment is a small but notable group. The GEM Report (2023) distinguishes between entrepreneurs driven by opportunity and those driven by necessity, and in a displacement scenario the latter is the more likely motivation. Government schemes such as PM Mudra Yojana exist to support exactly this group, though whether they are accessible or well-known to shop-floor manufacturing workers is a separate question.

The absence of higher education and early retirement from the responses is quietly significant. Higher education is financially and practically out of reach for most workers with family obligations and no income buffer. Early retirement requires pension provisions that simply do not exist for the majority of this sample.

6. Discussion

When taken together the findings of the study explicitly say that it is really hard to summarize what the automation research adjusts because these are not workers who are unaware of what is coming. Rather it is a story of people who are able to see the transition clearly, seeing the pressure of it, trying to get through it but with very less support than what the challenge demands for .

What workers understand, and what they do not?

Results

Demographic profile

The age distribution of the sample is proof that the manufacturing workers in India are relatively younger, since 70% of the sampled workers are in the age range of 20 to 39 years, which conforms to PLFS statistics (MoSPI, 2023). The gender distribution (87.8% male) is consistent with ASI figures indicating a 78-88% male dominance in heavy manufacturing (MoSPI, 2022). The educational qualification level is at the secondary education level for 76.8%, while 23.2% have received vocational and/or ITI training, which conforms to the PLFS findings.

According to sectors, 93.9% of the sample respondents are involved in manufacturing industries. This gives a very clear perspective on the automation process in India's manufacturing industry labor force. This conformity comes from the finding that the manufacturing industry is highly exposed to automation risks and McKinsey Global Institute predicts the potential of automation at 50-70% in manufacturing operations through demonstrated technology (MGI, 2017; 2022).

Awareness and understanding of automation

There was fragmentation in respondents' perceptions on the meaning of automation. Out of the total number of respondents, 36.6% viewed automation as purely mechanical replacement using robots, 31.7% considered automation as both software and machine replacements, while 31.7% viewed automation as a combination of digital devices, artificial intelligence and robotics. It is evident that there was a lack of awareness through training programs on automation but based on personal experience within production settings.

There was no uncertainty in any of the responses given, and this may be attributed to the pressure during face-to-face surveys (Podsakoff et al., 2003). This prevalence of displacement-focused definition implies that employees mostly relate to automation with respect to the displacement of jobs rather than complementariness (Acemoglu & Restrepo, 2019). This kind of perception could limit investment in skills improvement among the employees.

Perceived need for training

As per 75.6% of the respondents, there is a clear need for automation-related training with nobody thinking that the skills they possess currently are enough. Nonetheless, the participants have differing views regarding the intensity of the training required – 48.8% stated that they needed comprehensive training while 26.8% felt that just an introductory training would suffice. Additionally, 24.4% were not sure whether they needed comprehensive training or not (ILO, 2020).

The need for training mentioned by all the respondents is in sync with the forecasts of NSDC (2023), according to which there will be a big gap in digital manufacturing skills in 2026. But the difference in views on the intensity of training required indicates that the upskilling requirements differ among workers.

Perceived automation risk

In terms of risk perceptions, the distribution is remarkably dichotomous, with respondents almost equally divided into low (34.1%), moderate (32.9%), and very high (32.9%) risk groups concerning their current employment, even in a similar occupational environment. This can be explained by micro-level disparities in exposure to automation within production chains (Tversky & Kahneman, 1974).

Those in the very high risk category have consistently high automation anxiety (ILO, 2019) expressed in the answers to Q7-8 concerning the consequences of automation, making them a key target group for policy support in the form of retraining assurance, income protection, and employer communication. The low risk group is more challenging to understand; while some of them work in unautomatable occupations (Brynjolfsson & Mitchell, 2017), others might underestimate the risk of substitution.

Preferred adaptive responses

For instance, if their work was automated, those surveyed would either seek to get similar employment elsewhere (30.5%), accept low-paid employment to remain employed (29.3%), upskill through training at their current company (28.0%), or become self-employed (12.2%).

Clearly, this implies that there is no consensus among respondents about what needs to be done. There are different considerations for each choice made. Getting similar employment elsewhere presupposes that it even exists, and this becomes highly questionable in light of the automation wave throughout the industry (Acemoglu

& Restrepo, 2019). Accepting low-paid work is an honest account of lack of alternatives, yet one that may further inequality (ILO, 2018). Those preferring internal upskilling put quite a bit of trust into employer-led transition. Finally, while programs of self-employment such as Mudra do exist, it is unclear whether they are accessible for the displaced manufacturing workforce.

In any case, higher education or retirement are not included in the list of choices. While the former is financially out of reach for most, the latter requires pension provisions, which do not apply to this sample.

Discussion

Collectively, these findings paint a picture not just of a work force oblivious to an approaching danger, but of a work force that sees the transition coming, feels the pressure of it, and is trying to negotiate it with far fewer resources than the task requires.

That near-unanimity in engagement with the idea of automation is a result of a work force whose ideas are shaped largely by what it can see. Workers know what they can observe on the shop floor – the machines – but lack the means to understand the unseen algorithmic elements underlying it. This is not just a problem of knowledge. Acemoglu and Restrepo (2019) prove that the notion of automation as a force of displacement can undermine the very investments in upskilling that would make one less vulnerable to automation (Brynjolfsson & McAfee, 2014). Conceptual gaps have behavioural implications.

In addition, the workers face a dichotomy regarding productivity and displacement issues. While they see the efficiency, quality, and cost-effectiveness of automation, at the same time they are almost equally convinced that it will displace them from employment, increase the wage disparity based on skills, and train them at costs they cannot afford. This dichotomy is no paradox – the literature confirms this. According to Bessen et al. (2022), automation not only increases efficiency for firms but also results in higher worker separation and income losses, particularly for older and middle-educated workers, which is the prevalent educational level in this sample.

What is also interesting to remark is the unanimity of training demand per se. None of the respondents claimed that their skills were enough or automation did not relate to their job. At the same time, however, the sum of money workers are willing to spend on training does not cover the costs of a reliable programme because of low wage levels typical of semi-skilled labour. According to Cramarencu et al. (2023), despite being increasingly common, upskilling remains unaccompanied by adequate and affordable institutional solutions.

Weaved throughout the results of awareness, perceptions of risk, and training needs is the well-being aspect that the paper asserts is an integral part of the policy response process that should not be marginalized. The result that 32.9% of those surveyed perceive their exposure to automation as very high and that 29.3% of people would trade pay cuts for keeping jobs can be seen not only as indicators for the state of the labor market but also as manifestations of the economic and psychological stresses that have been identified in the well-being literature as factors leading to worsening mental health conditions and decreased quality of life (Nazareno & Schiff, 2021; Li et al., 2026).

Conclusion

The study focuses on automation awareness, perceptions of job risk, skills readiness, and well-being of workers in the industry sector in Jaipur, India. Results indicate a workforce which understands the issue of automation very well but has an incomplete conceptual understanding, has concerns about job security and does not have the required skills to upgrade themselves at the speed and scale that is needed.

A few results are noteworthy. Automation awareness stems more from experience on the factory floor rather than systematic awareness which leads to displacement-centric frames that may actually demotivate workers from upskilling. Workers perceive both the productive as well as negative impacts of automation on their job security, income security and costs of training. There is no doubt among workers about the need for upgrading their skills, however, there is a division in terms of whether this should be deep or shallow and also restricted by the wage-training costs mismatch. There is also no consensus on adaptive responses which range from job search, skill upgrading and entrepreneurship, indicating that there is no consistent strategy being followed by workers.

The implications of this work indicate a clear need for policies in terms of differentiated training, affordable upskilling funding, clear employer-led learning paths, and social safety networks geared towards the human burden of industrial change, rather than just the economic shock. Future research might include longitudinal studies of automation exposure and worker effects; case studies on particular exposed groups; evaluation of programs aimed at addressing such issues through reskilling and income support; business-level work examining how firms integrate automation and how workers talk about it; and well-being studies of automation transitions specifically including mental health and resilience programs.

There are no easy answers to the challenge of automation. As Kasy and Sautmann (2022) observe, the proper response will always be context-specific. The value of this paper lies in its attempt to define such context in light of the real-world responses of Indian manufacturing workers, in all their pragmatic concern and anxiety as they navigate an industry transformation which is difficult to characterize simply as "Industry 4.0".

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APPENDIX:

Q1. What is your age group? A. Under 20 years B. 20 – 29 years C. 30 – 39 years D. 40 – 49 years E. 50 – 59 years F. 60 years and above
Q.2 . What is your gender? A. Male B. Female C. Non-binary / Gender non-conforming D. Prefer not to say
Q.3 What is your highest level of education completed? A. High School / Secondary School (10th or 12th grade) A. Diploma / Vocational / ITI Certificate B. Bachelor's Degree (B.A. / B.Sc. / B.Com. / B.Tech. etc.) C. Postgraduate Degree (M.A. / M.Sc. / MBA / M.Tech. etc.)
Q4. How many years of professional work experience do you have? A. Less than 1 year B. 1-3 years C. 4-7 years D. 8-12 years E. 13-20 years F. More than 20 years
Q5. Which of the following best describes your primary job role / sector? A. Manufacturing / Production / Assembly B. Information Technology (IT) / Software / Data C. Banking, Finance & Insurance D. Healthcare / Pharmaceuticals E. Retail / Sales / Customer Service F. Logistics / Supply Chain / Warehousing G. Education / Training / Research H. Government / Public Administration I. Agriculture / Natural Resources

- Q6. How would you best describe automation in the context of your workplace?
- A. The use of software or machines to perform tasks that were previously done by humans
 - B. The use of robots in factories to replace manual labor
 - C. Any technology that helps speed up work (e.g., emails, spreadsheets, mobile apps)
 - D. Artificial intelligence (AI) systems that make decisions without human input
 - E. A combination of digital tools, AI, and robotics working together to replace or assist workers
 - F. I am not sure / I have limited knowledge of automation

- Q7. Do you feel you need additional training to understand or work effectively with automation technologies in your field?
- A. Yes — I strongly feel the need for training
 - B. Yes — but only basic/introductory training is sufficient
 - C. Uncertain — I am not sure what skills are required
 - D. No — my current skills are sufficient to adapt
 - E. No — automation is not relevant to my job role

- Q8. To what extent do you believe automation poses a risk of job loss in your current role or industry?
- A. Very High Risk — My job/industry is directly threatened by automation
 - B. Moderate Risk — Some tasks in my job could be automated, reducing headcount
 - C. Low Risk — Automation may assist but is unlikely to replace my role
 - D. No Risk — My role requires human judgement / creativity that cannot be automated
 - E. I am uncertain — I do not have enough information to assess this

- Q9. If automation significantly transforms your current job or makes it redundant, what would be your preferred course of action?
- A. Actively upskill / reskill to adapt to new digital roles within the same organisation
 - B. Seek a similar job at the same pay level in a different organisation or sector
 - C. Start my own business / freelance / become self-employed
 - D. Pursue higher education or a formal degree to qualify for advanced roles
 - E. Accept early retirement if financially feasible
 - F. Take any available job, even at a lower pay, to remain employed
 - G. I am unsure — I would wait and assess the situation as it develops

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