

Impact of Artificial Intelligence on the Economy and Employment:

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Abstract—Artificial Intelligence (AI) is reshaping production, business models and the nature of work. This study examines how people perceive the impact of AI on the economy and employment, using a structured online questionnaire completed by 71 respondents between 29 September and 2 October 2026. The sample was young (78.9% aged 18–25), predominantly male (63.4%), and drawn mainly from the IT sector (32.4%) and the student population (28.2%). Data were analyzed through frequency distributions, cross-tabulations, Pearson chi-square tests with Monte Carlo permutation p-values, Cramér’s V, and Spearman rank correlation. Respondents were largely optimistic: 94.4% agreed that AI improves economic productivity and 90.1% viewed its overall impact as positive. Yet 84.5% expected AI to reduce traditional jobs to some or a great extent, and job displacement was the most frequently cited concern (50.7%). At the same time, 77.5% believed AI would create new employment opportunities, 90.1% felt employees must learn new skills, and technical or digital skills were ranked most important (63.4%). Overall sentiment was significantly associated with familiarity with AI ($V = 0.43$), gender ($V = 0.37$) and the perceived effect of AI on employee productivity ($V = 0.40$), but not with age, education or sector. The findings point to a “transformation rather than replacement” view of AI that is consistent with recent IMF, ILO and World Economic Forum evidence, and underline the central role of reskilling. The small, non-probability sample limits generalization.

I. INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the present era, influencing economies, businesses, industries, and the nature of employment across the world. AI refers to the development of computer systems capable of performing tasks that traditionally require human intelligence, such as learning, reasoning, problem-solving, decision-making, language processing, and pattern recognition. The rapid development of generative AI, machine learning, robotics, and automation has accelerated the adoption of AI in

sectors such as finance, healthcare, manufacturing, education, retail, transportation, and information technology.

The impact of AI on the economy is significant because it can increase productivity, reduce operational costs, improve decision-making, and create new products and services. Businesses can use AI to analyse large volumes of data, automate repetitive activities, predict market trends, personalize customer experiences, and optimize their resources. These developments can contribute to economic growth and create new business opportunities. At the same time, the adoption of AI may create challenges for organizations and economies, particularly in terms of investment requirements, technological inequality, data security, and the changing demand for skills.

Employment is another major area affected by AI. Automation can perform certain routine and repetitive tasks more efficiently, potentially reducing the demand for some existing job roles. However, AI can also generate new employment opportunities in areas such as data science, AI development, cybersecurity, cloud computing, AI ethics, and technology management. Many existing jobs are also expected to change rather than disappear completely, requiring workers to develop new technical, analytical, creative, and interpersonal skills. Consequently, continuous learning and reskilling have become increasingly important for employees.

Overall, AI represents both an opportunity and a challenge for the modern economy and workforce. Its long-term impact will depend on how governments, businesses, educational institutions, and workers adapt to technological change. Responsible adoption, investment in education and skills, and appropriate policies can help ensure that the benefits of AI

contribute to sustainable economic development and inclusive employment opportunities.

II. PROBLEM STATEMENT

The rapid adoption of Artificial Intelligence is transforming economic activities and the employment landscape by automating tasks, changing job roles, and creating new opportunities. The key challenge is to understand AI's impact on productivity, economic growth, job displacement, and the changing skill requirements of the workforce.

III. OBJECTIVE

The main objective of this study is to examine the impact of Artificial Intelligence on the economy and employment in the present era. It aims to understand how AI is transforming industries, improving productivity, changing job roles, and creating new employment opportunities. The study also focuses on the challenges faced by workers and organizations due to increasing automation and technological development.

- To analyze the effect of AI on economic growth and business productivity.
- To identify job roles that are being transformed or automated by AI.
- To examine the emergence of new AI-related employment opportunities.
- To understand the importance of reskilling and upskilling for workers.
- To identify the major challenges and opportunities associated with AI adoption.

IV. LITERATURE REVIEW

Artificial Intelligence (AI) has become an important area of research due to its growing influence on economic activities and employment. Previous studies suggest that AI can significantly improve productivity by automating routine tasks, supporting decision-making, and enabling businesses to use resources more efficiently. Research by the International Monetary Fund (IMF) has highlighted that AI may affect a substantial share of jobs globally, with both job displacement and increased productivity depending on the nature of work and level of AI adoption (Cazzaniga et al., 2024). Similarly, studies by

the International Labour Organization (ILO) indicate that generative AI is more likely to transform many occupations rather than completely replace human workers (Gmyrek et al., 2023).

Several researchers have also emphasized the importance of skills development. As AI adoption increases, demand is expected to grow for technical, analytical, digital, creative, and interpersonal skills. At the same time, workers performing highly repetitive tasks may face greater employment risks. The literature therefore presents AI as both an opportunity and a challenge for the workforce. Overall, existing research indicates that the economic and employment effects of AI will depend on technological adoption, workforce adaptation, education, reskilling, and appropriate economic and labour policies.

Table 1: Table of Literature Review

Author(s) and year	Focus and method	Key findings	Relevance to the present study
Cazzaniga et al. (2024), International Monetary Fund	Estimates how much employment is exposed to AI across global income groups and considers whether AI is likely to complement or displace workers.	Nearly 40% of global employment is exposed to AI. Exposure is higher in advanced economies, where some jobs may benefit from AI complementarity while others face lower labour demand.	Provides a global context for examining respondents' expectations about job displacement and the sectors most affected by AI. IMF study
Gmyrek, Berg, and Bescond (2023), International Labour Organization	Assesses the potential exposure of occupations to generative AI and its effects on job quantity	The authors conclude that generative AI is more likely to augment many occupations than to automate them	Supports the study's focus on job transformation, employment concerns, and differences in perceptions by gender.

	and quality.	entirely. Clerical work is especially exposed, with possible gendered effects because women are overrepresented in many clerical roles.	ILO working paper
Brynjolfsson, Li, and Raymond (2023)	Studies the introduction of an AI conversational assistant among 5,179 customer-support agents.	Access to the tool increased issues resolved per hour by 14% on average. Gains were greatest for novice and lower-skilled workers, while experienced and highly skilled workers saw minimal impact.	Offers workplace-level evidence on productivity and uneven effects across workers, which can be compared with respondents' views about AI and employee productivity. NBER working paper
Acemoglu (2025)	Uses a task-based economic framework to estimate the possible economy-wide productivity effects of AI.	The estimated productivity gains over a ten-year period are nontrivial but modest, and may be overstated because early evidence comes from tasks that are easier to learn and measure.	Adds a macroeconomic perspective and helps distinguish expected workplace productivity improvements from economy-wide growth.

World Economic Forum (2025)	Surveys employers about expected changes to jobs and skills through 2030.	Employers project 170 million jobs created and 92 million displaced by 2030, for a net increase of 78 million. Skills gaps are identified as a major barrier to business transformation, and many employers expect job skills to change.	Relates directly to the study's questions about new employment opportunities, job displacement, and the need for reskilling. Future of Jobs Report 2025
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4.1 Exposure of Jobs to AI

The IMF estimates that almost 40% of global employment is exposed to AI, with exposure of about 60% in advanced economies, 40% in emerging-market economies and 26% in low-income countries, largely because advanced economies have more cognitive-task-oriented jobs (Cazzaniga et al., 2024). Roughly half of the exposed jobs in advanced economies may benefit from AI complementarity, while the other half face the risk of lower labour demand, lower wages or reduced hiring. The same analysis suggests that college-educated workers are better placed to move into AI-complementary roles, whereas older workers may find adaptation harder. The ILO's global analysis of generative AI reaches a similar conclusion in terms of augmentation: the dominant effect is expected to be to augment occupations rather than automate them outright, with the largest impact in high- and upper-middle-income countries because of their larger share of clerical work, which is an important source of female employment and therefore produces gendered effects (Gmyrek et al., 2023).

4.2 Productivity and Economic Growth

Micro-level evidence is encouraging. In a study of 5,179 customer-support agents, access to a generative AI assistant raised the number of issues resolved per hour by 14% on average, and by 34% for novice and

low-skilled workers, with minimal impact on experienced workers (Brynjolfsson et al., 2023). Macroeconomic estimates are more cautious. Acemoglu (2025), using a task-based framework, concludes that the aggregate gains in total factor productivity over a ten-year horizon are nontrivial but modest, and cautions that early evidence is drawn from easy-to-learn tasks. The literature therefore suggests that perceived and measured productivity gains at the worker level need not translate one-for-one into economy-wide growth.

4.3 Job Creation, Displacement and Skills

The World Economic Forum's Future of Jobs Report 2025, based on a survey of more than 1,000 employers, projects that 170 million new jobs will be created and 92 million displaced by 2030, a net gain of 78 million jobs and a churn equal to 22% of today's formal employment (World Economic Forum, 2025). Skills gaps are named as the main barrier to business transformation by 63% of employers, and nearly 40% of the skills required in the workforce are expected to change. Around 41% of surveyed employers anticipated workforce reductions where AI can automate tasks. Taken together, these studies frame AI as a force that simultaneously destroys and creates jobs, with reskilling as the main adjustment mechanism.

4.4 Research Gap

Most of the above evidence is based on occupational task data or employer surveys. Far less is known about how individual workers, students and early-career professionals perceive these changes, and whether perceptions differ by familiarity with AI, gender, education or sector. This study addresses that gap by collecting primary survey data on public perceptions of AI's economic and employment impact and examining how those perceptions vary across respondent characteristics and across one another.

V. PROPOSED METHODOLOGY

5.1 Research Design

The study adopts a quantitative, cross-sectional, descriptive and inferential survey design. A cross-sectional design captures respondents' perceptions at a single point in time, which suits an exploratory examination of a fast-moving topic. The analysis

combines descriptive statistics (to profile opinions) with inferential tests (to examine whether opinions differ by respondent characteristics and by one another).

5.2 Instrument and Variables

Primary data were collected with a structured online questionnaire of 15 items. After a name field (used only to avoid duplicate entries and excluded from all analysis and reporting), four items captured respondent characteristics (age category, gender, highest educational qualification and working sector), one captured familiarity with AI, and nine closed-ended items captured perceptions of AI's effect on productivity, sectors, jobs, skills, productivity at the employee level, employment concerns and overall impact. All items are categorical; most are ordinal (for example, "Strongly agree" to "Disagree"). Table 1 maps each objective of the study to the questionnaire items that address it.

Table 2: Mapping of study objectives to questionnaire items

Objective	Questionnaire items
1. Effect of AI on economic growth and business productivity	Q7 (AI improving economic productivity); Q13 (effect on employee productivity)
2. Job roles transformed or automated by AI	Q8 (sector most affected); Q9 (reduction in traditional jobs)
3. Emergence of new AI-related employment opportunities	Q10 (AI creating new employment opportunities)
4. Importance of reskilling and upskilling	Q11 (most important skill); Q12 (need to learn new skills)
5. Challenges and opportunities of AI adoption	Q14 (biggest concern); Q15 (overall view of impact)
Respondent profile and moderating conditions	Q2–Q5 (age, gender, education, sector); Q6 (familiarity with AI)

5.3 Sample and Data Collection

Responses were gathered through a non-probability (convenience) sample distributed online. Between 29 September and 2 October 2026, 71 complete responses were received. No duplicate respondents were found,

and no record had missing values, so all 71 responses were retained. Respondent names were removed before analysis to preserve anonymity.

5.4 Research Hypotheses

Based on the literature and the study objectives, the following hypotheses were examined:

1. H1: Familiarity with AI is associated with the respondent's overall view of AI's impact.
2. H2: Respondents who expect AI to reduce traditional jobs differ in their belief that AI will create new employment opportunities (the "transformation" hypothesis).
3. H3: The perceived effect of AI on employee productivity is associated with the overall view of AI's impact.
4. H4: Overall view of AI's impact differs by age, gender, education and working sector.
5. H5: The belief that employees must learn new skills is associated with the skill respondents rank as most important.

5.5 Tools and Techniques

Data cleaning, coding and statistical analysis were carried out in Python using pandas (McKinney, 2010) and SciPy (Virtanen et al., 2020), and all charts were produced with Matplotlib (Hunter, 2007). The techniques used were: (i) frequency and percentage distributions for every question; (ii) cross-tabulations, shown as 100% stacked bar charts, for condition-wise analysis; (iii) Pearson's chi-square test of independence; (iv) Cramér's V as the effect-size measure; and (v) Spearman's rank correlation between ordinal familiarity and ordinal overall view (Agresti, 2013).

VI. SYSTEM ARCHITECTURE

Because this is a survey-based study rather than a software system, the "system architecture" refers to the end-to-end research framework that converts raw questionnaire responses into findings. The framework (Figure 1) has five stages: instrument design, data collection, data preparation, an analysis engine, and interpretation against the literature.

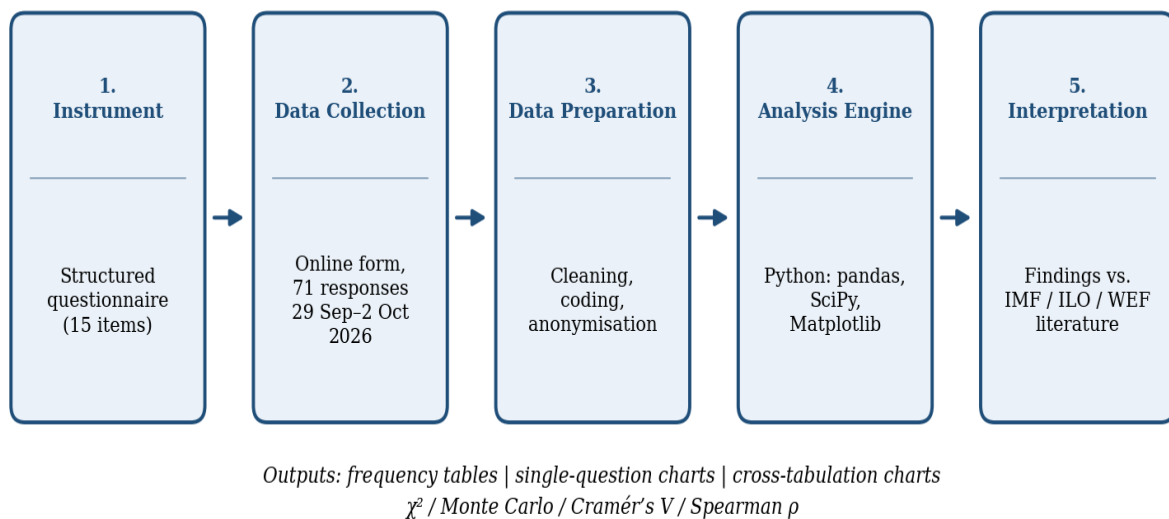


Figure 1: Research framework: from questionnaire to interpreted findings

In the data-preparation stage, response labels were shortened for display (for example, "Bachelor's Degree (e.g., B.A., B.Sc., B.Tech, B.Com)" became "Bachelor's"), ordinal items were assigned a natural order, and names were removed. The analysis engine

produced one chart per question and one chart per cross-tabulation, together with the test statistics reported in Section 8. Interpretation then compared the observed patterns with the IMF, ILO, WEF and academic evidence reviewed in Section 4.

VII. EVALUATION STRATEGY

The results are evaluated on four criteria.

Descriptive adequacy. Each question is summarized by counts and percentages of all 71 respondents, and each cross-tabulation by row percentages with the group size (n) shown, so that readers can see how much weight each group can bear.

Statistical significance. Associations are tested with Pearson's chi-square test at a 5% significance level. Because many of the cross-tabulations contain cells with expected counts below five (between 33% and 86% of cells), the asymptotic chi-square approximation may be unreliable. Each test is therefore also evaluated by a Monte Carlo permutation test (2,000 random permutations of the response variable, fixed random seed), and a result is described as significant only when the permutation p-value is below .05. Both p-values are reported.

Effect size. Statistical significance depends strongly on sample size, so Cramér's V is reported to show the strength of association. As a rough guide, values near 0.10 indicate a weak, near 0.30 a moderate and 0.50 or above a strong association, with the exact thresholds depending on table size (Cohen, 1988).

Validity and limitations. The questionnaire items were designed to map directly to the study objectives (Table 1), which supports content validity. Because 16 condition-wise tests are examined, the possibility of chance findings is acknowledged, and a Bonferroni-adjusted threshold ($.05 \div 16 = .003$) is discussed in Section 8.5 together with the other limitations of the study.

VIII. RESULTS AND DISCUSSION

8.1 Respondent Profile

Table 2 and Figure 2 describe the 71 respondents. The sample is young, with 56 respondents (78.9%) in the 18–25 age group, and male-dominated (45 men, 63.4%, and 26 women, 36.6%). Two-thirds hold a bachelor's degree (66.2%). The largest occupational groups are IT and software (32.4%) and students or

those not currently employed (28.2%), followed by banking, finance and insurance (15.5%) and healthcare and pharmaceuticals (9.9%). Because of this composition, the results are best read as the views of a young, technology-aware group rather than of the general workforce.

Table 3: Profile of respondents (N = 71)

Variable	Category	n	%
Age category	18–25	56	78.9
	26–30	7	9.9
	31–35	7	9.9
	41–45	1	1.4
Gender	Male	45	63.4
	Female	26	36.6
Education	Bachelor's degree	47	66.2
	High school / secondary	11	15.5
	Master's degree	8	11.3
	Diploma / associate degree	3	4.2
	Other	2	2.8
Sector	IT & software	23	32.4
	Student / not currently employed	20	28.2
	Banking, finance & insurance	11	15.5
	Healthcare & pharmaceuticals	7	9.9
	Other	5	7.0
	Manufacturing & engineering	4	5.6
	Retail & e-commerce	1	1.4

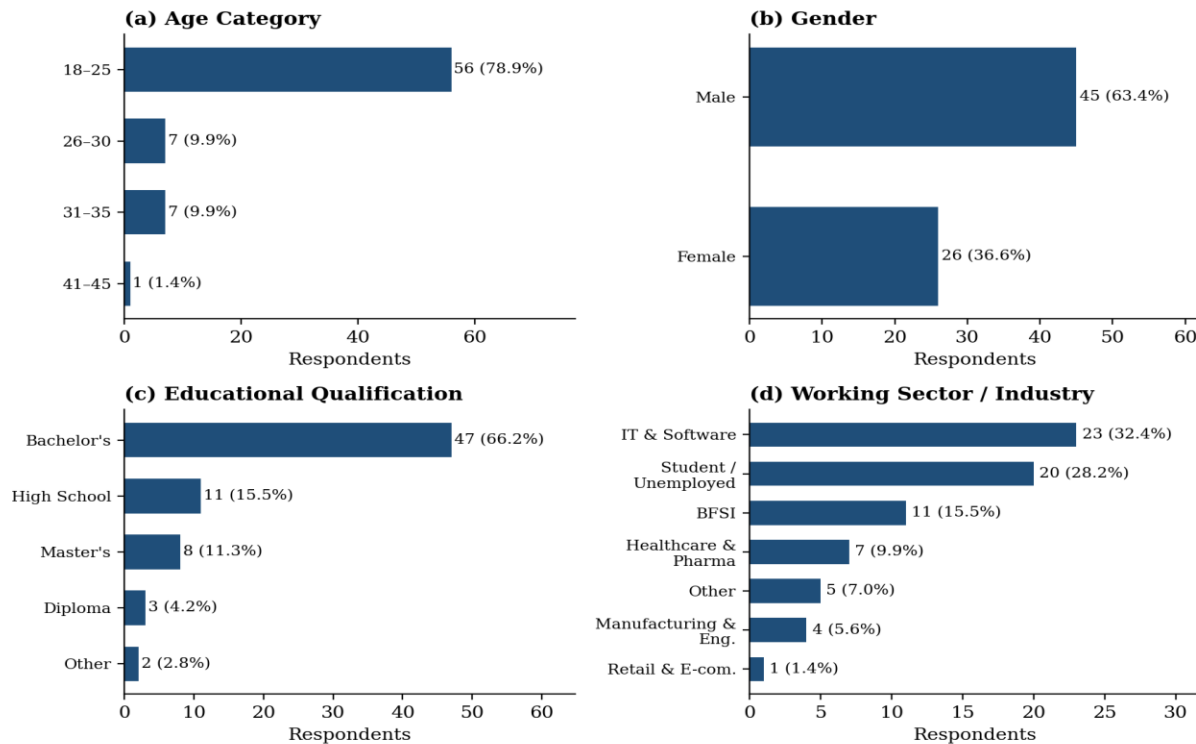


Figure 2: Respondent profile: (a) age, (b) gender, (c) education and (d) working sector (Questions 2–5)

8.2 Question-wise Analysis

This section presents the distribution of responses to each of the perception questions (Questions 6–15). Table 3 summarizes the leading response to each question.

Table 4: Summary of leading responses to Questions 6–15

Question	Leading response	n (%)	Combined favourable / affirmative
Q6 Familiarity with AI	Very familiar	48 (67.6%)	85.9% (very + somewhat)
Q7 AI improving productivity	Strongly agree	35 (49.3%)	94.4% (agree + strongly agree)
Q8 Sector most affected	Information Technology	57 (80.3%)	—
Q9 AI reducing traditional jobs	To some extent	33 (46.5%)	84.5% (some + great extent)

Question	Leading response	n (%)	Combined favourable / affirmative
Q10 AI creating new jobs	Strongly agree	28 (39.4%)	77.5% (agree + strongly agree)
Q11 Most important skill	Technical / digital	45 (63.4%)	—
Q12 Need to learn new skills	Definitely	46 (64.8%)	90.1% (definitely + probably)
Q13 Effect on employee productivity	Significantly increase	32 (45.1%)	81.7% (moderately + significantly)
Q14 Biggest concern	Job displacement	36 (50.7%)	—
Q15 Overall view	Mostly positive	33 (46.5%)	90.1% (mostly + highly positive)

Question 6: Familiarity with AI

Most respondents described themselves as well informed: 48 (67.6%) were very familiar with AI, 13 (18.3%) somewhat familiar and 9 (12.7%) slightly familiar, while only one respondent (1.4%) was not familiar at all (Figure 3). With 85.9% at least somewhat familiar, the opinions recorded below are largely informed ones, although this also suggests the sample over-represents people who already follow technology.

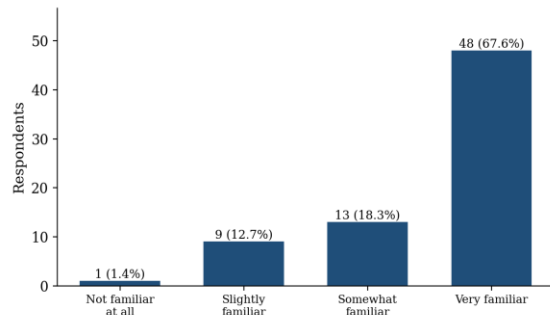


Figure 3: Familiarity with Artificial Intelligence (Q6)

Question 7: Is AI improving economic productivity?

Agreement was almost universal. Thirty-five respondents (49.3%) strongly agreed and 32 (45.1%) agreed, a combined 94.4%, while only 4 (5.6%) disagreed and none strongly disagreed (Figure 4). This matches worker-level evidence such as the 14% average productivity gain reported by Brynjolfsson et al. (2023). It is, however, more optimistic than the macroeconomic estimates of Acemoglu (2025), which suggest that economy-wide gains will be real but modest; respondents' perceptions of productivity may therefore reflect what they see in their own work more than aggregate outcomes.

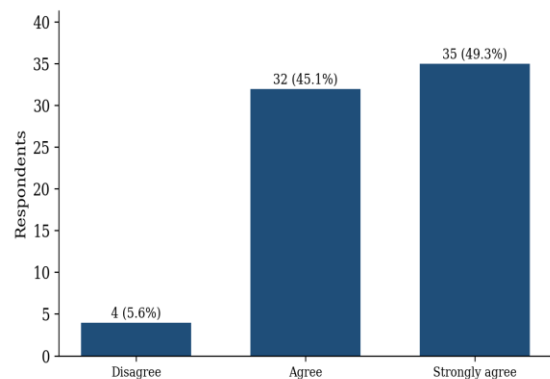


Figure 4: Perception of AI improving economic productivity (Q7)

Question 8: Sector most affected by AI

Information Technology was named by 57 respondents (80.3%), far ahead of manufacturing (6; 8.5%), banking and finance (5; 7.0%) and healthcare (3; 4.2%) (Figure 5). Because 32.4% of the sample works in IT and many others are students of technical subjects, this may partly reflect the respondents' own vantage point. The direction is nevertheless consistent with the IMF's finding that cognitive-task-intensive occupations are the most exposed (Cazzaniga et al., 2024).

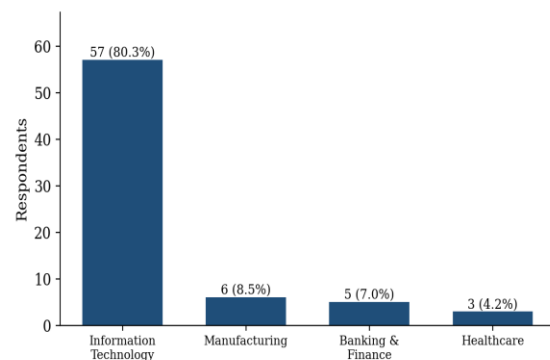


Figure 5: Sector perceived as most affected by AI (Q8)

Question 9: Will AI reduce the number of traditional jobs?

Most respondents expect some job loss: 33 (46.5%) said AI will reduce traditional jobs to some extent and 27 (38.0%) to a great extent, a combined 84.5%, whereas 11 (15.5%) said very little (Figure 6). The scale of expected displacement is in line with the IMF's exposure estimates and with the 92 million jobs the WEF projects will be displaced by 2030, but the preference for "to some extent" over "to a great extent" suggests that many see partial rather than wholesale loss.

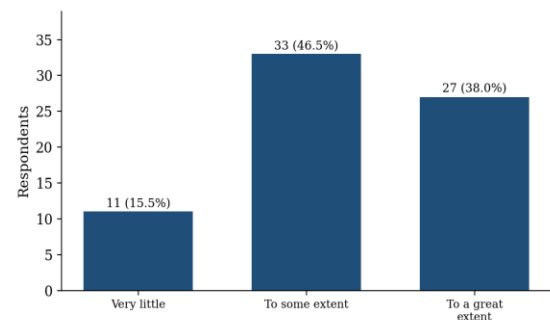


Figure 6: Expected reduction in traditional jobs due to AI (Q9)

Question 10: Will AI create new employment opportunities?

Twenty-eight respondents (39.4%) strongly agreed and 27 (38.0%) agreed that AI will create new employment opportunities (77.5% in total), while 15 (21.1%) disagreed and one (1.4%) strongly disagreed (Figure 7). Belief in job creation is thus strong but less unanimous than belief in productivity gains: more than one in five respondents are not convinced that new roles will materialise. The WEF's projection of a net gain of 78 million jobs by 2030 supports the majority view, but also depends on workers being able to move into the new roles.

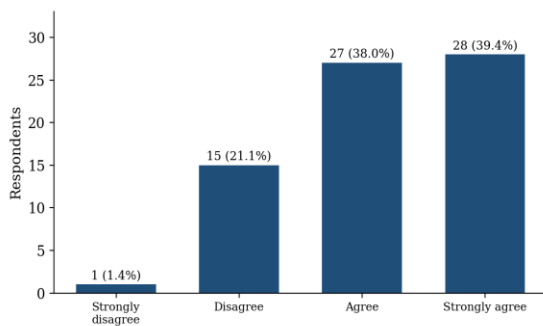


Figure 7: Belief that AI will create new employment opportunities (Q10)

Question 11: Most important skill in an AI-driven workplace

Technical or digital skills were selected by 45 respondents (63.4%), followed by analytical skills (13; 18.3%), creative or problem-solving skills (8; 11.3%) and communication skills (5; 7.0%) (Figure 8). Respondents therefore see AI primarily as a technical challenge to be met with technical capability, and give comparatively little weight to the creative and interpersonal skills that the literature also expects to grow in demand.

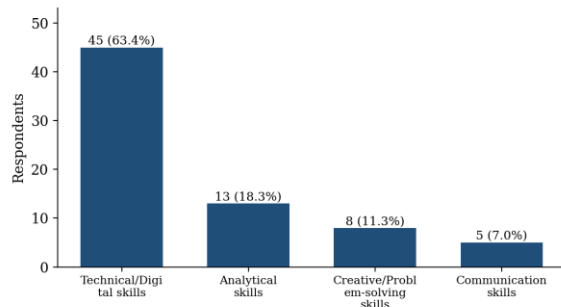


Figure 8: Skill considered most important in an AI-driven workplace (Q11)

Question 12: Do employees need to learn new skills because of AI?

Forty-six respondents (64.8%) answered “Definitely” and 18 (25.4%) “Probably”, so 90.1% believe that new skills are needed; only 6 (8.5%) answered “Probably not” and 1 (1.4%) “Not at all” (Figure 9). This is the most one-sided result in the survey after the productivity question and confirms the importance of reskilling and upskilling, which is the fourth objective of this study. It also mirrors employers’ view that skills gaps are the main barrier to business transformation (World Economic Forum, 2025).

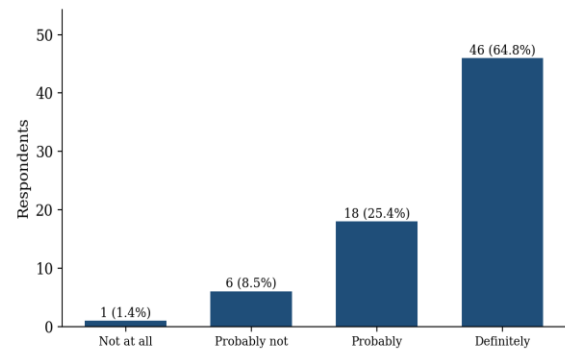


Figure 9: Perceived need for employees to learn new skills (Q12)

Question 13: Effect of AI on employee productivity

A total of 32 respondents (45.1%) expect AI to increase employee productivity significantly and 26 (36.6%) moderately (81.7% combined). Eleven respondents (15.5%) expect little impact and 2 (2.8%) expect productivity to decrease (Figure 10). The minority who expect little or negative impact is a reminder that gains are uneven; Brynjolfsson et al. (2023) found that benefits were concentrated among less experienced workers and minimal for experienced ones.

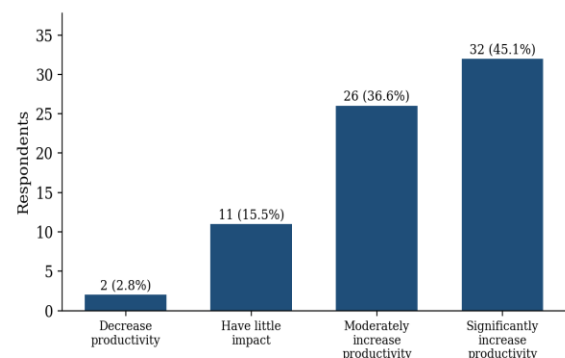


Figure 10: Expected effect of AI on employee productivity (Q13)

Question 14: Biggest concern regarding AI and employment

Job displacement is the leading concern (36 respondents; 50.7%), followed by skill gaps (22; 31.0%), wage reduction (7; 9.9%) and increased workplace dependency on technology (6; 8.5%) (Figure 11). Together, displacement and skill gaps account for 81.7% of responses, indicating that respondents are worried less about the technology itself than about whether workers can keep their jobs and adapt to new requirements.

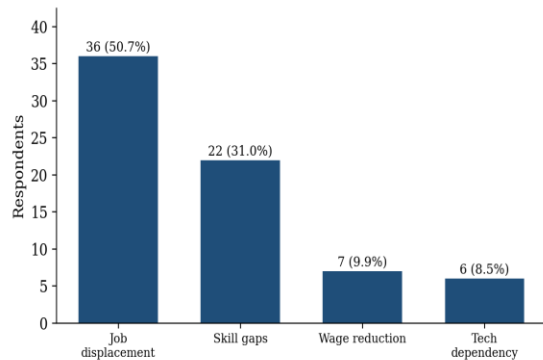


Figure 11: Biggest concern regarding AI and employment (Q14)

Question 15: Overall view of the impact of AI

Overall sentiment is clearly positive: 33 respondents (46.5%) view the impact as mostly positive and 31 (43.7%) as highly positive (90.1% combined), while 7 (9.9%) view it as mostly negative (Figure 12). No respondent recorded a highly negative view. Positive sentiment sits alongside strong awareness of displacement risk (Questions 9 and 14), which suggests a view of AI as beneficial but disruptive.

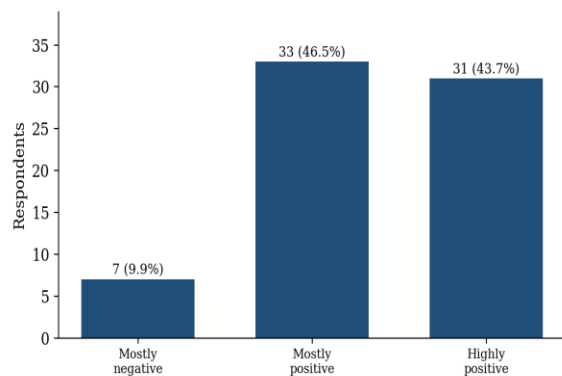


Figure 12: Overall view of the impact of AI on the economy and employment (Q15)

8.3 Condition-wise Analysis

The charts below show how responses to selected questions vary by respondent condition: familiarity, demographic characteristics, working sector, and other attitudes. Each bar shows the percentage distribution within a group, with the group size (n) in the label. Several groups are very small (for example, one respondent aged 41–45 and one in retail), so group-level percentages should be read as descriptive only. Test statistics are collected in Table 4 at the end of this section.

8.3.1 By Familiarity with AI

Familiarity and productivity (Q6 × Q7). Strong agreement that AI improves productivity rises with familiarity: 11.1% of the slightly familiar group, 30.8% of the somewhat familiar group and 60.4% of the very familiar group strongly agreed (Figure 13). Among the very familiar, 97.9% agreed or strongly agreed. The association is borderline and not significant at the 5% level ($\chi^2(6) = 12.52$, $p = .051$, Monte Carlo $p = .079$, $V = 0.30$).

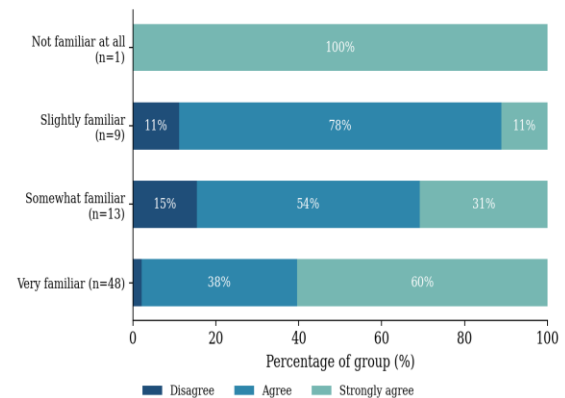


Figure 13: Belief that AI improves productivity, by familiarity with AI (Q6 × Q7)

Familiarity and overall view (Q6 × Q15). This is the strongest relationship in the data. Five of the nine respondents (55.6%) who were only slightly familiar with AI held a mostly negative view, compared with none of the 13 somewhat familiar respondents and 2 of the 48 very familiar respondents (4.2%) (Figure 14). Half of the very familiar group (50.0%) held a highly positive view versus 11.1% of the slightly familiar group. The association is significant ($\chi^2(6) = 26.21$, $p < .001$, Monte Carlo $p < .001$, $V = 0.43$), and the ordinal correlation between familiarity and overall view is positive and significant (Spearman $\rho = 0.30$, p

= .010). Hypothesis H1 is therefore supported. The data cannot show the direction of the relationship: familiarity may reduce apprehension, or more optimistic people may be more likely to learn about AI. The slightly familiar group is also small (n = 9).

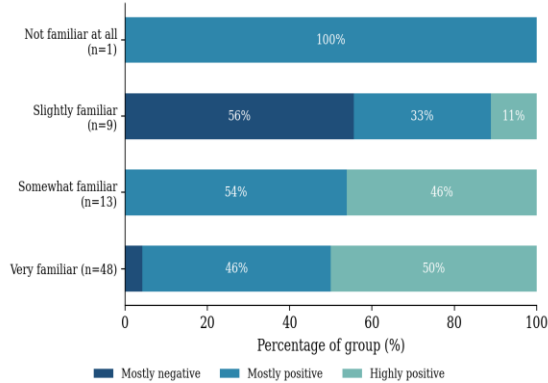


Figure 14: Overall view of AI, by familiarity with AI (Q6 x Q15)

Familiarity and job reduction (Q6 x Q9). Expectation of job reduction is widespread at every level of familiarity: 85.4% of the very familiar, 92.3% of the somewhat familiar and 77.8% of the slightly familiar expect AI to reduce traditional jobs to some or a great extent (Figure 15). There is no significant difference ($\chi^2(6) = 7.27$, $p = .297$, Monte Carlo $p = .311$, $V = 0.23$), suggesting that concern about displacement does not depend on how well a person knows AI.

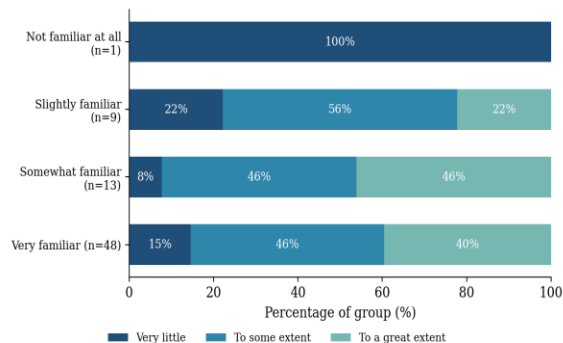


Figure 15: Expected reduction in traditional jobs, by familiarity with AI (Q6 x Q9)

Familiarity and need for new skills (Q6 x Q12). The belief that employees “definitely” need new skills is held by 68.8% of the very familiar, 53.8% of the somewhat familiar and 55.6% of the slightly familiar (Figure 16), but the difference is not significant ($\chi^2(9) = 9.17$, $p = .422$, Monte Carlo $p = .358$, $V = 0.21$). The need for reskilling is a broadly shared view.

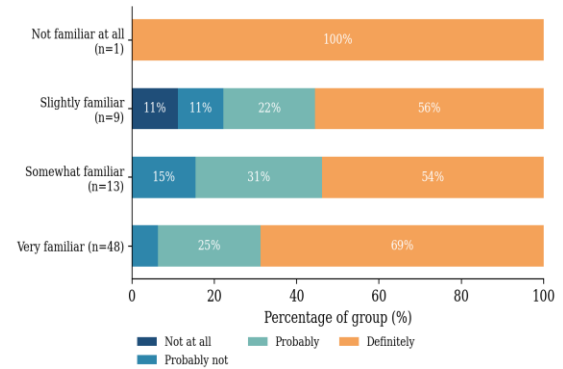


Figure 16: Perceived need to learn new skills, by familiarity with AI (Q6 x Q12)

8.3.2 By Demographic Characteristics

Age and overall view (Q2 x Q15). Positive sentiment is higher in the older groups: 71.4% of respondents aged 31–35 and 57.1% of those aged 26–30 held a highly positive view, compared with 37.5% of those aged 18–25 (Figure 17). The 18–25 group also contains most of the mostly negative responses (6 of 7). However, the groups other than 18–25 contain only 15 respondents between them, and the difference is not significant ($\chi^2(6) = 5.48$, $p = .484$, Monte Carlo $p = .400$, $V = 0.20$).

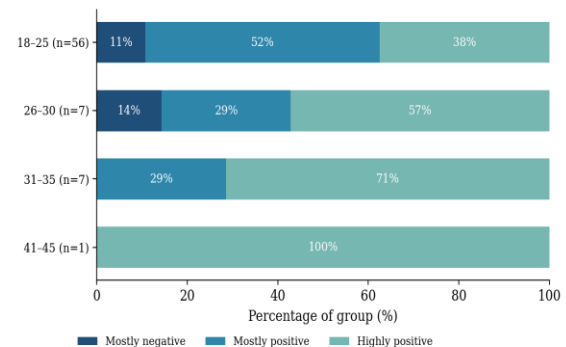


Figure 17: Overall view of AI, by age category (Q2 x Q15)

Gender and overall view (Q3 x Q15). Gender shows a significant association with overall sentiment ($\chi^2(2) = 9.51$, $p = .009$, Monte Carlo $p = .008$, $V = 0.37$). Among women, 23.1% held a mostly negative view, against 2.2% of men, and six of the seven mostly negative respondents were women (Figure 18). The share holding a highly positive view was similar (46.2% of women and 42.2% of men); the difference therefore lies in the negative tail and in men’s greater tendency to choose “mostly positive” (55.6% versus

30.8%). One possible explanation, which this survey cannot test, is the ILO's finding that generative AI exposure is concentrated in clerical occupations, which are a major source of female employment (Gmyrek et al., 2023). The sample contains only 26 women, so this result should be confirmed in a larger sample. It supports H4 for gender only.

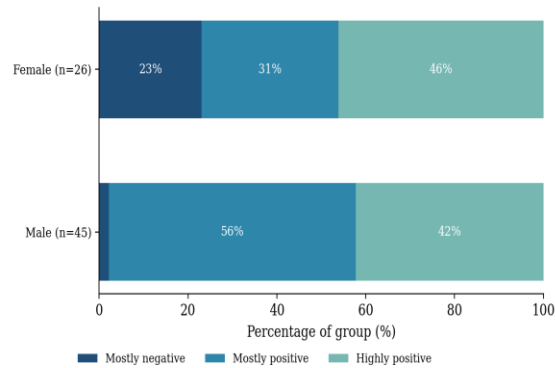


Figure 18: Overall view of AI, by gender (Q3 × Q15) Education and overall view (Q4 × Q15). There is no clear gradient by education (Figure 19). Respondents with a master's degree (n = 8) were all positive (75.0% mostly positive, 25.0% highly positive), while bachelor's degree holders (n = 47) were 10.6% mostly negative and high-school respondents (n = 11) were 63.6% highly positive. The differences are not significant ($\chi^2(8) = 6.84$, $p = .554$, Monte Carlo $p = .580$, $V = 0.22$), and the diploma (n = 3) and "other" (n = 2) groups are too small for comment.

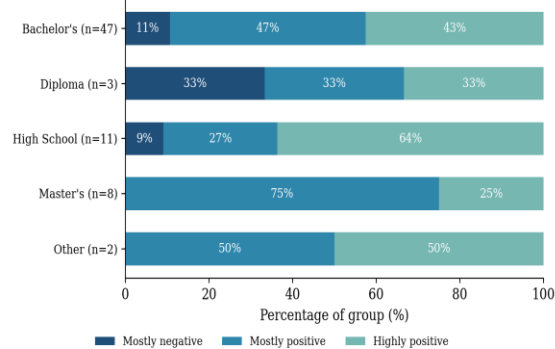


Figure 19: Overall view of AI, by educational qualification (Q4 × Q15)

Gender and most important skill (Q3 × Q11). Women were more likely than men to name technical or digital skills as most important (76.9% versus 55.6%), while men gave more weight to analytical (22.2% versus 11.5%) and creative or problem-solving skills (15.6% versus 3.8%) (Figure 20). The difference is not

significant ($\chi^2(3) = 4.24$, $p = .236$, Monte Carlo $p = .235$, $V = 0.24$).

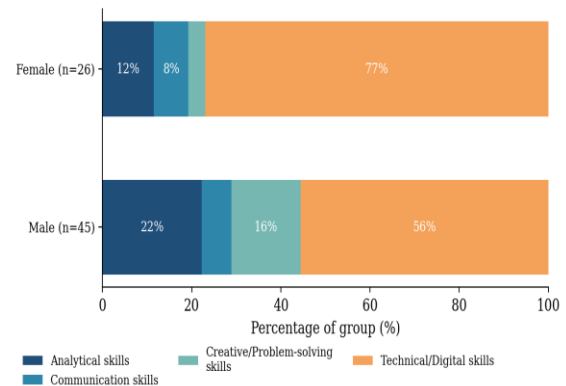


Figure 20: Most important skill, by gender (Q3 × Q11)

8.3.3 By Working Sector

Sector and overall view (Q5 × Q15). Overall sentiment was most positive in IT and software, where 52.2% held a highly positive view and only 4.3% a mostly negative one (Figure 21). Students and those not currently employed were the least positive group (20.0% mostly negative; 25.0% highly positive); four of the seven mostly negative respondents belong to this group. The differences are not significant ($\chi^2(12) = 11.48$, $p = .488$, Monte Carlo $p = .476$, $V = 0.28$).

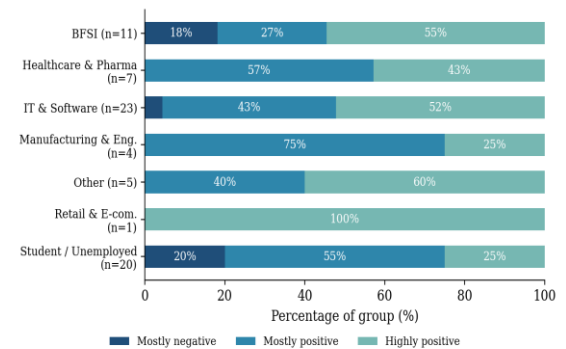


Figure 21: Overall view of AI, by working sector (Q5 × Q15)

Sector and job reduction (Q5 × Q9). Expectations of job reduction differ visibly across sectors (Figure 22). In banking, finance and insurance, 72.7% said AI will reduce traditional jobs to a great extent, compared with 43.5% in IT, 14.3% in healthcare and 15.0% among students. This pattern fits the IMF's observation that cognitive-task-intensive work is highly exposed (Cazzaniga et al., 2024), but with groups of between 7

and 23 respondents the difference is not statistically significant ($\chi^2(12) = 17.00$, $p = .150$, Monte Carlo $p = .149$, $V = 0.35$).

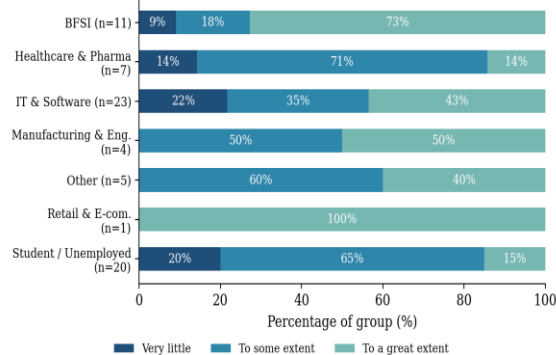


Figure 22: Expected reduction in traditional jobs, by working sector (Q5 x Q9)

Sector and job creation (Q5 x Q10). Strong belief that AI will create jobs was highest in IT (52.2% strongly agree) and BFSI (45.5%) and lowest in healthcare (14.3%, although 71.4% agreed) and among students (25.0%) (Figure 23). There is no significant association ($\chi^2(18) = 13.70$, $p = .749$, Monte Carlo $p = .696$, $V = 0.25$).

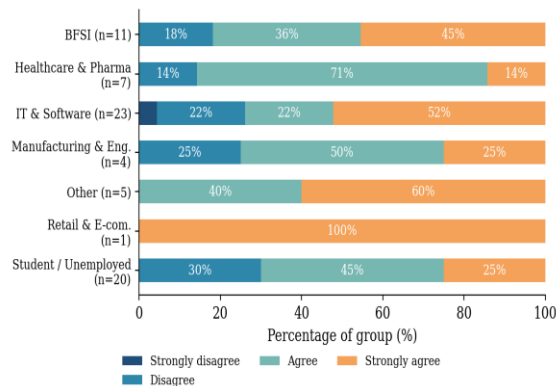


Figure 23: Belief that AI will create new jobs, by working sector (Q5 x Q10)

Sector and main concern (Q5 x Q14). Job displacement was the leading concern in IT (56.5%), BFSI (54.5%), manufacturing (50.0%) and among students (45.0%), whereas skill gaps led in healthcare (57.1%, or 4 of 7 respondents) (Figure 24). Wage reduction was cited by 18.2% of BFSI and 40.0% of “other” respondents (2 of 5). The association is not significant ($\chi^2(18) = 14.72$, $p = .681$, Monte Carlo $p = .682$, $V = 0.26$).

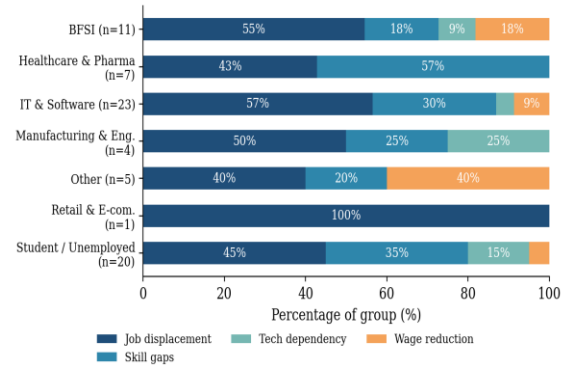


Figure 24: Biggest concern regarding AI and employment, by working sector (Q5 x Q14)

8.3.4 By Related Attitudes

Job reduction and job creation (Q9 x Q10). Respondents' views on job loss and job creation are significantly related ($\chi^2(6) = 16.05$, $p = .013$, Monte Carlo $p = .005$, $V = 0.34$), but not in the direction a simple trade-off would imply. Among those who expect AI to reduce jobs to a great extent, 59.3% strongly agreed that AI will also create new jobs, whereas among those who expect very little reduction, 45.5% disagreed that AI will create new jobs (Figure 25). In total, 49 respondents (69.0%) both expect job reduction (to some or a great extent) and agree that new jobs will be created. This supports H2 and indicates that respondents see AI as a powerful force of change that removes some jobs and creates others, rather than as a technology with little employment impact.

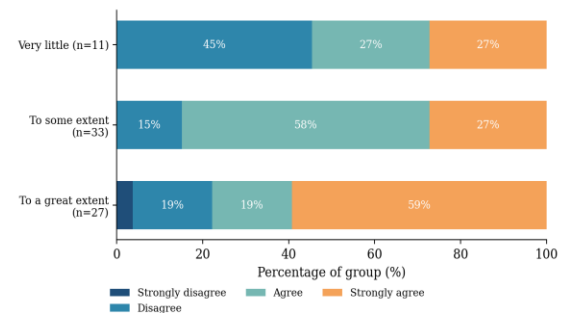


Figure 25: Belief in job creation, by expected job reduction (Q9 x Q10)

Job reduction and overall view (Q9 x Q15). Expecting large job losses does not translate into a negative overall view ($\chi^2(4) = 11.11$, $p = .025$, Monte Carlo $p = .023$, $V = 0.28$). Among those expecting a great reduction, 63.0% held a highly positive view, versus

24.2% of those expecting some reduction and 54.5% of those expecting very little (Figure 26). The proportion with a mostly negative view is similar in all three groups (9.1% to 11.1%), so the differences are in the intensity of positive sentiment, not its direction.

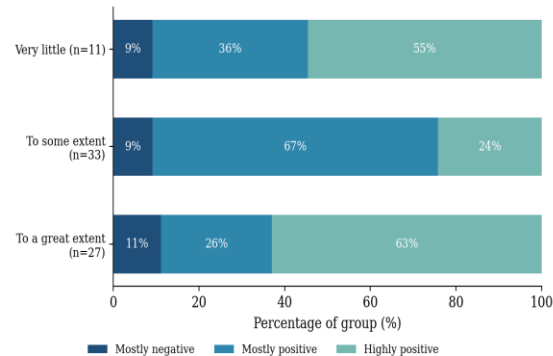


Figure 26: Overall view of AI, by expected job reduction (Q9 x Q15)

Need for new skills and most important skill (Q12 x Q11). Respondents who said employees “definitely” need new skills overwhelmingly named technical or digital skills as most important (73.9%), compared with 50.0% of those who said “probably” (Figure 27). This association is significant ($\chi^2(9) = 21.50$, $p = .011$, Monte Carlo $p = .024$, $V = 0.32$) and supports H5, but 75% of cells have expected counts below five and the “probably not” and “not at all” groups contain only 7 respondents, so the result should be treated with caution.

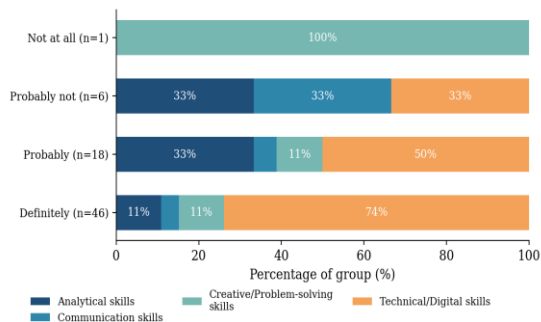


Figure 27: Most important skill, by perceived need to learn new skills (Q12 x Q11)

Productivity effect and overall view (Q13 x Q15). The expected effect of AI on employee productivity is strongly related to overall sentiment ($\chi^2(6) = 22.75$, $p < .001$, Monte Carlo $p = .005$, $V = 0.40$). Of the 32 respondents expecting a significant productivity increase, 59.4% held a highly positive view and none a mostly negative one, while 45.5% of the 11

respondents expecting little impact held a mostly negative view (Figure 28). Five of the seven mostly negative respondents expect little impact on productivity. This supports H3: people who do not see AI delivering productivity benefits in the workplace are the ones most likely to take a negative overall view.

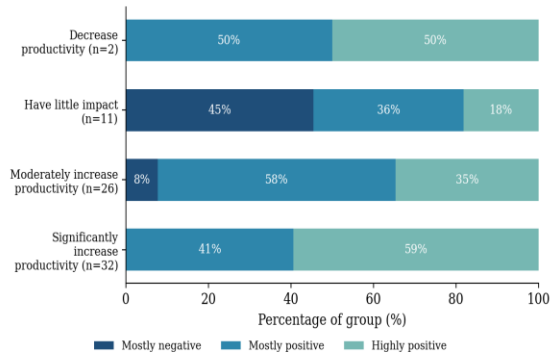


Figure 28: Overall view of AI, by expected effect on employee productivity (Q13 x Q15)

8.3.5 Summary of Statistical Tests

Table 5: Chi-square tests of association for condition-wise analysis

Cross-tabulation	χ^2	d f	p	M C p	V	Cel ls E< 5	Result (MC p<.05)
Familiarity x Productivity improvement (Q6xQ7)	12.52	6	.051	.079	0.30	67%	Not significant
Familiarity x Overall view (Q6xQ15)	26.21	6	<.001	<.001	0.43	67%	Significant
Familiarity x Job reduction (Q6xQ9)	7.27	6	.297	.311	0.23	67%	Not significant
Familiarity x Need new skills (Q6xQ12)	9.17	9	.422	.358	0.21	75%	Not significant

Cross-tabulation	χ^2	df	p	MC p	V	Cells E<5	Result (MC p<.05)
Age × Overall view (Q2×Q15)	5.48	6	.484	.400	0.20	75%	Not significant
Gender × Overall view (Q3×Q15)	9.51	2	.009	.008	0.37	33%	Significant
Education × Overall view (Q4×Q15)	6.84	8	.554	.580	0.22	80%	Not significant
Gender × Important skill (Q3×Q11)	4.24	3	.236	.235	0.24	50%	Not significant
Sector × Overall view (Q5×Q15)	11.48	12	.488	.476	0.28	76%	Not significant
Sector × Job reduction (Q5×Q9)	17.00	12	.150	.149	0.35	76%	Not significant
Sector × Job creation (Q5×Q10)	13.70	18	.749	.696	0.25	86%	Not significant
Sector × Main concern (Q5×Q14)	14.72	18	.681	.682	0.26	82%	Not significant
Job reduction × Job creation (Q9×Q10)	16.05	6	.013	.005	0.34	50%	Significant
Job reduction × Overall view (Q9×Q15)	11.11	4	.025	.023	0.28	44%	Significant

Cross-tabulation	χ^2	df	p	MC p	V	Cells E<5	Result (MC p<.05)
Need new skills × Important skill (Q12×Q11)	21.50	9	.011	.024	0.32	75%	Significant
Productivity effect × Overall view (Q13×Q15)	22.75	6	<.001	.005	0.40	58%	Significant

Note: MC p = Monte Carlo permutation p-value (2,000 permutations); V = Cramér's V; "Cells E<5" = share of cells with expected count below 5.

Table 6: Outcome of hypothesis tests

Hypothesis	Evidence	Outcome
H1 Familiarity ↔ overall view	Q6×Q15: MC p = .001, V = 0.43; Spearman ρ = 0.30 (p = .010)	Supported
H2 Job reduction ↔ job creation	Q9×Q10: MC p = .005, V = 0.34	Supported
H3 Productivity effect ↔ overall view	Q13×Q15: MC p = .005, V = 0.40	Supported
H4 Overall view differs by age, gender, education, sector	Gender significant (MC p = .009); age (.400), education (.580), sector (.476) not significant	Partially supported (gender only)
H5 Need for new skills ↔ most important skill	Q12×Q11: MC p = .024, V = 0.32 (sparse cells)	Supported, with caution

8.4 Discussion

Three main themes emerge from the results when set against the existing literature.

Optimism alongside awareness of disruption. Respondents are overwhelmingly positive about AI (90.1%) and believe it raises productivity (94.4%), yet 84.5% expect traditional jobs to fall and half name displacement as their main concern. The data show that these views coexist rather than conflict: 69.0% of respondents expect both job reduction and job creation, and those expecting the greatest reduction are among the most positive overall. This mirrors the “transformation, not replacement” conclusion of the ILO (Gmyrek et al., 2023) and the simultaneous creation and displacement forecast by the WEF (2025).

Knowledge and experienced benefit shape sentiment. The strongest associations in the data are between overall view and familiarity with AI ($V = 0.43$) and between overall view and the expected effect on employee productivity ($V = 0.40$). Negative sentiment is concentrated among people who know little about AI or who expect little productivity benefit from it. These results suggest that visible, practical benefits and basic AI literacy may be the most direct ways to build confidence in AI, although the cross-sectional design cannot establish causation.

Reskilling is seen as the adjustment mechanism, and it is mainly technical. With 90.1% saying new skills are needed and 63.4% choosing technical or digital skills as the most important, respondents place the burden of adaptation on skills acquisition. The survey also shows that skill gaps are the second most common concern (31.0%), in line with the employer view that skills gaps are the main barrier to transformation (World Economic Forum, 2025). The low priority given to communication (7.0%) and creative skills (11.3%) is a point educators and employers may wish to address, since the literature expects a mix of technical, analytical, creative and interpersonal skills to be valuable.

Differences by gender deserve attention. Women were far more likely than men to hold a mostly negative view (23.1% versus 2.2%), which is consistent with the ILO’s observation that effects of generative AI are gendered, but the survey did not collect occupation-level data that could confirm this explanation.

8.5 Limitations

Several limitations should be kept in mind. First, the sample is small ($N = 71$), non-probabilistic, and concentrated among young, male, IT-sector and student respondents, so the findings cannot be generalized to the Indian or global workforce. Second, many cross-tabulation cells are sparse, which reduces statistical power and makes group-level percentages unstable; the permutation tests mitigate but do not remove this problem. Third, 16 condition-wise tests were run, so a few significant results may be due to chance: with a Bonferroni-adjusted threshold of .003, only the association between familiarity and overall view (MC $p = .001$) would remain significant, and the other significant results should be regarded as indicative. Fourth, all measures are self-reported perceptions, not observed outcomes, and the cross-sectional design prevents causal conclusions. Finally, some questions asked respondents to choose a single sector, skill or concern, which masks respondents who hold several views.

IX. KEY CONCEPTUAL OBSERVATIONS

1. Transformation, not replacement. Most respondents (69.0%) simultaneously expect AI to reduce some jobs and create others, so AI is seen as a reshaper of work rather than a pure job destroyer.
2. Optimism is conditional on experience. Positive sentiment is greatest among those who are familiar with AI and expect productivity benefits; mostly negative views cluster among those with little familiarity (55.6% of the slightly familiar) or little expected productivity gain (45.5%).
3. Productivity is the bridge to economic optimism. Almost all respondents (94.4%) agree that AI raises productivity, and no respondent who expects a significant productivity increase held a negative overall view.
4. Displacement fear is widespread but does not dominate sentiment. Job displacement is the top concern (50.7%) and is expected to occur to some or a great extent by 84.5%, yet 90.1% remain positive overall.
5. Reskilling is the shared answer. 90.1% believe employees must learn new skills, regardless of familiarity with AI, and 63.4% see technical or digital skills as the most important.

6. Exposure is perceived unevenly. Respondents in banking, finance and insurance were most likely to expect large job reductions (72.7%), and 80.3% of respondents see IT as the most affected sector, which suggests that cognitive, data-intensive work is seen as the most exposed.
7. A gender gap in sentiment exists. Women were markedly more likely to hold a mostly negative view, a pattern that merits further investigation with larger samples and occupation data.

X. CONCLUSION

This study examined perceptions of the impact of AI on the economy and employment using survey data from 71 respondents. Against the five objectives, the findings are as follows. First, respondents believe AI is improving economic and employee productivity (94.4% and 81.7% respectively), in line with firm-level evidence, although macroeconomic studies suggest the aggregate effect may be more modest. Second, 84.5% expect traditional jobs to be reduced to some or a great extent, and IT, followed at some distance by manufacturing and banking and finance, is seen as the most affected sector. Third, 77.5% believe AI will create new employment opportunities, and those who expect the greatest job loss are also the most likely to expect job creation. Fourth, 90.1% believe employees must learn new skills, with technical and digital skills ranked most important. Fifth, the main challenges identified are job displacement (50.7%) and skill gaps (31.0%), while the main opportunity is the perceived productivity gain, and overall sentiment is positive for 90.1% of respondents.

Statistically, sentiment about AI is associated with familiarity, gender and expected productivity effects, but not with age, education or sector in this sample. These results suggest that policies and organizational practices that raise AI literacy, deliver tangible workplace benefits, and provide accessible reskilling pathways are likely to build support for AI adoption. Because the sample is small and not representative, the conclusions should be treated as exploratory evidence rather than population estimates.

XI. FUTURE WORK

- Replicate the study with a larger, probability-based sample that includes more women, older

workers, workers in non-technical occupations and respondents from rural areas and different regions.

- Add questions on occupation, seniority, actual use of AI tools at work and perceived personal job risk, so that the gender and sector differences observed here can be explained rather than only described.
- Use ordinal logistic regression or similar multivariable models to test the effects of familiarity, gender, productivity expectations and sector simultaneously.
- Include open-ended questions and interviews to understand why respondents who expect large job losses remain optimistic.

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