

**Original Research Article**

# Artificial Intelligence and the Transformation of Finance Jobs in India: Evidence from Online Job-Market Data

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**Abstract**

This study examines how artificial intelligence (AI) is reshaping demand for finance labour in India, using exclusively secondary, publicly verifiable evidence drawn from online job-market trackers and official sources. The analysis synthesises monthly hiring indices (Naukri JobSpeak; foundit Insights Tracker), AI-posting share trackers (Indeed), skills projections (World Economic Forum), task-based exposure measures (International Labour Organization; International Monetary Fund; OECD), and India-specific labour-survey research based on the Periodic Labour Force Survey, together with Government of India, Reserve Bank of India and NASSCOM documents. Reported indicators are compared descriptively and across finance-related occupational groups; no new microdata are collected, and the few calculations performed by the author are explicitly labelled as such. Three findings stand out. First, AI-related hiring in India has consistently outgrown aggregate white-collar hiring, with reported year-on-year growth in AI/ML roles of 25-42 per cent during 2024-2026 against flat or negative comparator segments. Second, exposure is highly uneven across finance occupations: routine clerical and front-office roles (bank tellers, data entry, accounting and bookkeeping) are concentrated at the automation-exposed end, while fintech engineering, AI/data specialist and compliance-oriented roles are expanding. Third, most evidence supports task-level augmentation rather than occupational substitution, implying that transformation, not wholesale job destruction, is the central policy problem. The paper discusses implications for finance professionals,

higher education and skills policy, and states its limitations, including the absence of publicly available raw Indian job-posting microdata.

**Keywords:** artificial intelligence; finance jobs; banking; FinTech; online job postings; skills; India; labour market transformation

## 1. Introduction

Artificial intelligence (AI) has moved from a research agenda to a general-purpose technology whose labour-market consequences are now measurable in real time. Unlike previous automation waves, which affected primarily manual and routine production work, machine learning and especially generative AI operate directly on information, text and decision support, the core raw material of financial services (Brynjolfsson & Mitchell, 2017; Eloundou et al., 2024). Consequently, banking, insurance, accounting, investment intermediation and financial technology (FinTech) are among the sectors where debates about augmentation, substitution and job transformation are most consequential. For India, a country whose digital economy is expanding rapidly and whose services sector anchors export growth, the question of how AI is changing the demand for finance labour is both academically important and policy-relevant.

India provides an unusually informative setting for studying AI-driven occupational change in finance. The Reserve Bank of India (RBI) reports that India now accounts for nearly half (48.5 per cent) of global real-time payments volume, reflecting an extraordinary digitalisation of financial transactions (Reserve Bank of India, 2024a). The Union Cabinet approved the IndiaAI Mission in March 2024 with an outlay of INR 10,371.92 crore, including a dedicated IndiaAI FutureSkills pillar (Press Information Bureau, 2024). NASSCOM estimates that India's technology industry employed about 5.43 million people in financial year 2023-24 and generated revenue of about USD 254 billion, with a growing share of this workforce serving banking and financial-services clients (NASSCOM, 2024); industry revenue was subsequently projected to rise to about USD 282.6 billion in FY2024-25, with net hiring of about 126,000 (Reuters, 2025). At the same time, Indian labour-market institutions generate a rich public stream of online job-market data: monthly hiring indices from Naukri.com and foundit, AI-posting trackers from Indeed, and skills rankings from LinkedIn, complemented by official statistics from the Periodic Labour Force Survey (PLFS) and regulatory reports.

This paper asks what these genuine, publicly verifiable data sources reveal about the transformation of finance jobs in India under AI. It deliberately refrains from speculative modelling: no proprietary datasets are used, no raw job postings are scraped, and no statistical results are imputed. Instead, the study assembles a documented evidence base covering the period 2018-2026, compares reported indicators across sources and occupational groups, and interprets them through the task-based framework of technological change (Acemoglu & Restrepo, 2019). Throughout, exposure to AI is treated as neither synonymous with job loss nor with job gain; the empirical literature itself is divided, with some studies finding no clear employment effects of AI exposure and others finding augmentation or displacement in specific niches (Georgieff & Hye, 2021; World Bank, 2025).

The paper makes three contributions. First, it provides, to the best of our knowledge, the first structured, source-verified synthesis of India's online job-market evidence on AI and finance occupations, with every quantitative claim traced to an identifiable public document. Second, it maps the evidence onto finance sub-sectors, banking, accounting, insurance, investment and FinTech, which India-specific studies typically treat as an

undifferentiated BFSI block. Third, it translates the evidence into concrete implications for finance professionals and higher education, a segment where employability data indicate persistent skill gaps (Wheebox, 2024). The remainder of the paper is organised as follows: Section 2 reviews the literature; Section 3 develops the theoretical framework; Section 4 identifies the research gap; Section 5 states the objectives; Section 6 describes data sources and methodology; Section 7 presents results; Section 8 discusses them; Section 9 draws implications; Section 10 acknowledges limitations; and Section 11 concludes.

## **2. Literature Review**

### **2.1 Technological change and labour demand: from computerisation to the task-based paradigm**

The modern debate on automation and employment began with predictions of mass computerisation. Frey and Osborne (2017) estimated the susceptibility of 702 detailed US occupations to computerisation and concluded that about 47 per cent of total US employment was at high risk, with employment in production, administrative and clerical occupations most exposed. Subsequent scholarship qualified this pessimism. Autor (2015) documented why automation has historically not eliminated the majority of jobs: machines substitute for labour in routine codifiable tasks but complement workers in problem-solving, adaptability and creativity, while productivity gains raise demand in non-automated activities. Deming (2017) showed that, in the United States, the share of jobs requiring high levels of social interaction grew by nearly 12 percentage points between 1980 and 2012, while math-intensive but less-social jobs shrank, a pattern that anticipates the premium on human interaction in AI-saturated service work.

The analytical core of this literature is now the task-based model. Acemoglu and Restrepo (2019) formalise technology's effect on labour demand as the net of a displacement effect, whereby machines take over tasks previously performed by workers, and a reinstatement effect, whereby new tasks in which labour holds a comparative advantage are created. Automation always reduces labour's share in value added and may reduce labour demand even as productivity rises, unless new task creation is sufficiently strong. Empirically, Acemoglu and Restrepo (2020) find that one additional industrial robot per thousand workers reduced the US local employment-to-population ratio by about 0.2 percentage points and wages by about 0.42 per cent, establishing that displacement effects are real but technology- and task-specific rather than uniform. Brynjolfsson and Mitchell (2017) argue that, for machine learning specifically, the suitable unit of analysis is the task rather than the job, because most occupations bundle automatable and non-automatable tasks.

### **2.2 Measuring AI exposure: ability, task and posting-based approaches**

A second strand of literature operationalises AI exposure. Felten, Raj and Seamans (2021) construct the AI Occupational Exposure (AIOE) score by linking 52 application-level AI abilities to the abilities required by occupations, providing an occupation-, industry- and geography-level measure that has been adapted by, among others, the OECD and the IMF. Eloundou et al. (2024) estimate the labor-market impact potential of large language models (LLMs) by classifying tasks against LLM capabilities: they find that roughly 1.8 per cent of jobs could have over half of their tasks affected by LLMs with simple interfaces, rising to just over 46 per cent when LLM-complementary software is considered, and that exposure spans all wage levels with higher-income, higher-education jobs more exposed. The International Labour Organization's index of exposure to generative AI shows that, globally, only clerical work is highly exposed, with 24 per cent of clerical tasks in the high-exposure category and a further 58 per cent at medium exposure, while other occupational groups show high exposure of only 1-4 per

cent; the dominant potential effect is augmentation, that is, automating some tasks within an occupation while leaving time for other duties (Gmyrek et al., 2023; United Nations News, 2023). The ILO's refined 2025 index, built from 52,558 worker and expert data points on 2,861 tasks, confirms substantial but uneven potential automation of tasks (International Labour Organization [ILO], 2025).

Cross-country evidence counsels caution before equating exposure with job loss. Georgieff and Hye (2021), extending the Felten et al. measure to 23 OECD countries, find no clear relationship between AI exposure and employment growth over 2012-2019, and, importantly, find that in occupations with high computer use, greater AI exposure is associated with higher employment growth. The OECD Employment Outlook 2023 concludes that occupations at highest risk of automation have not declined faster since the rise of machine learning and that labour demand in AI-exposed occupations has not (yet) slowed, while the AI workforce itself more than tripled between 2012 and 2019 (OECD, 2023). The International Monetary Fund (IMF; Cazzaniga et al., 2024) estimates that almost 40 per cent of global employment is exposed to AI, with exposure of about 60 per cent of employment in advanced economies, 40 per cent in emerging markets and 26 per cent in low-income countries, and emphasises that exposure can cut both ways: it may complement or substitute for workers depending on task composition and complementary investments.

### 2.3 Evidence from online job postings and firm-level experiments

Because occupational exposure measures are static, a growing literature uses online job postings to observe demand for AI skills as it changes. Alekseeva et al. (2021), analysing millions of US vacancy records, show that demand for AI skills is distinct from demand for general ICT skills: it is concentrated in larger firms, in specific sectors and in jobs combining technical and managerial content, and commands a wage premium. Firm-level and field experiments document the augmentation channel. Brynjolfsson, Li and Raymond (2025), studying the staggered introduction of a generative-AI conversational assistant among about 5,200 customer-support agents, find a 15 per cent average productivity increase, with the largest gains for novice and low-skilled workers, and evidence that the tool disseminates the practices of the most able workers. Noy and Zhang (2023) find in randomised experiments on professional writing tasks that ChatGPT reduced average time taken by 40 per cent and raised output quality by 18 per cent, with inequality between workers narrowing. Both studies illustrate task-level augmentation rather than headcount elimination.

Job-posting trackers provide the most current, if less controlled, evidence. Indeed's Hiring Lab documents that the share of postings mentioning generative AI rose about 3.5-fold in the United States within a year and faster elsewhere, that data analytics consistently has the highest generative-AI posting share across the nine countries analysed, and that sectors such as insurance exhibit generative-AI usage below expectations (Indeed Hiring Lab, 2024). Its later analyses show that generative AI remains rarely mentioned in white-collar postings, including accounting, despite substantial capability overlap (Indeed Hiring Lab, 2025a), that about 26 per cent of postings are highly and 54 per cent moderately transformable, with almost half of the skills in a typical posting poised for hybrid transformation, while none of more than 2,800 assessed skills is very likely to be fully replaced (Indeed Hiring Lab, 2025b), and that software-development postings have rebounded with AI-fluent, senior roles driving the gains (Indeed Hiring Lab, 2026).

### 2.4 India-specific evidence on AI, employment and skills

India-specific scholarship is younger but growing. The ILO and the Institute for Human Development report that India's employment challenge remains structural: youth account for a very large share of the unemployed,

educational attainment has risen faster than the quality of employment, and the educated young face increasingly difficult school-to-work transitions (International Labour Organization & Institute for Human Development, 2024); the report highlights, for instance, that young people aged 15-29 accounted for almost 83 per cent of India's unemployed workforce in 2022, a figure that became the subject of public contestation between the ILO and official sources (The Economic Times, 2024). Using seven waves of the PLFS from 2018-19 to 2024-25, Mahajan, Sharma, Wadhwa and Ahmed (2026) document job polarisation in India: employment growth concentrated in low-skilled occupations with modest growth in some high-skilled professional roles and near-stagnation in medium-skilled occupations; nearly half of the increase in non-farm wage employment came from occupations in the least AI-exposed fifth, while high-skilled cognitive occupations, though most exposed to AI, continued to add jobs. The World Bank's South Asia analysis likewise finds that AI adoption is already reducing employment in specific, highly exposed niche categories (for example, online freelance writing and translation) while complementing workers elsewhere (World Bank, 2025). Policy analyses frame AI as an opportunity: NITI Aayog's National Strategy for Artificial Intelligence, citing Accenture's estimate that AI could add USD 957 billion to India's economy by 2035, positions AI as a growth multiplier for sectors including financial services (NITI Aayog, 2018; Accenture, 2017).

Industry and skills reports fill in the demand side. Deloitte's India skills research, released with NASSCOM, projects Indian AI talent demand to more than double from about 600,000-650,000 in 2022 to over 1.25 million by 2027, with AI skills supply growing at roughly 13 per cent against AI market demand growth of 25-35 per cent per year, and reports that 43 per cent of the Indian workforce had used AI in their organisations in the preceding year (Deloitte, 2024). TeamLease Digital's Digital Skills and Salary Primer estimates that the AI talent gap in India could reach 53 per cent by 2026 (Entrepreneur India, 2025). Wheebox's India Skills Report 2024 places overall youth employability at 51.25 per cent, up from 40.44 per cent in 2017 (Wheebox, 2024; Press Information Bureau, 2025). These sources collectively suggest that in India the binding constraint is less the quantity of jobs than the supply of AI-complementary skills, the question this paper investigates for the finance sector specifically.

### 3. Theoretical Framework

The study is anchored in the task-based theory of technological change (Acemoglu & Restrepo, 2019). In this framework, output is produced from a continuum of tasks allocated between capital and labour. Advances in AI expand the set of tasks that capital, here software, models and intelligent agents, can perform, generating a displacement effect on labour demand. Simultaneously, three countervailing forces operate: a productivity effect, whereby cheaper task execution expands output and thus demand for non-automated tasks; a capital deepening effect; and a reinstatement effect, whereby entirely new tasks, occupations and skill bundles are created in which labour has a comparative advantage, for example prompt engineering, model validation, AI governance, data curation and human-machine interaction design (Acemoglu & Restrepo, 2019; WEF, 2025).

Applied to finance, the framework yields three analytically distinct scenarios that the empirical literature treats as separable (Gmyrek et al., 2023; Cazzaniga et al., 2024). Substitution occurs when the automatable task share of an occupation is high and complementary investments are weak, as in transaction processing, cash handling, document verification and routine bookkeeping. Augmentation occurs when AI raises the productivity of the human worker within the same occupation, as documented in customer support (Brynjolfsson et al., 2025) and professional writing (Noy & Zhang, 2023); here employment may persist or even expand while job content, and hence skill requirements, transform. Reinstatement occurs when AI creates new roles, as in FinTech engineering and AI/data specialisation, which the WEF (2025) identifies among the fastest-growing roles globally through 2030.

The framework therefore predicts heterogeneous outcomes within finance: exposure is a property of tasks, not of the 'finance' label, and observed posting data should show simultaneous contraction signals in routine clerical occupations and expansion signals in AI-adjacent ones.

The framework is coupled to a demand-side measurement model. Online job postings proxy employer labour demand: the frequency of skill terms and of AI-related titles in postings indexes the AI-intensity of new hiring (Alekseeva et al., 2021), and hiring indices built from posting counts index the level of white-collar demand. Because postings capture gross hiring rather than net employment, they are best interpreted as indicators of the direction and composition of demand change, not of headcount outcomes; this interpretation constraint is made explicit in the methodology and limitations.

#### 4. Research Gap

Three gaps motivate this study. First, the international literature on AI exposure is rich, but India-specific empirical evidence remains thin and fragmented: exposure indices (Felten et al., 2021; Eloundou et al., 2024) have not been systematically applied to Indian finance occupations in peer-reviewed work, and the principal India-specific analysis to date (Mahajan et al., 2026) examines the whole economy rather than the finance sector. Second, existing India-focused discussions of AI and jobs rely heavily on policy narratives or single-source industry statistics; a cross-source synthesis that confronts hiring-index evidence (Naukri, foundit, Indeed), skills projections (WEF), task-exposure research (ILO, IMF, OECD) and official Indian data (PLFS, RBI, NITI Aayog, PIB, NASSCOM) is missing. Third, finance is typically analysed as an undifferentiated BFSI aggregate, masking differences between, for example, bank teller work and fintech engineering that theory says should be stark. By assembling a fully traceable, multi-source evidence base and mapping it onto finance sub-sectors and occupations, this paper addresses all three gaps within the limits of publicly available data.

#### 5. Objectives and Research Questions

The overall objective of the study is to assess, using verifiable secondary data, how AI is transforming the demand for finance labour in India in terms of the level, composition and skill content of hiring. Five research questions (RQs) structure the analysis, each answerable from the documented evidence base described in Section 6.

RQ1. How has demand for AI-related roles and skills evolved in India's labour market, and within it the finance sector, during 2023-2026?

RQ2. How are AI and digital skill requirements changing in finance occupations, and what does the evidence say about emerging versus declining skills?

RQ3. How does AI exposure and transformation differ across banking, accounting, insurance, investment and FinTech occupations?

RQ4. What do the data imply about the relative importance of augmentation, substitution and task transformation, as against simple job destruction, in Indian finance employment?

RQ5. What are the implications for finance professionals, higher education and skills policy in India?

## 6. Data Sources and Methodology

### 6.1 Evidence base: datasets and documents

The study uses exclusively secondary data that are publicly accessible and independently verifiable. Table 1 inventories the principal sources, their coverage and their underlying methodologies. Two families of sources are combined. The first comprises online job-market trackers: the Naukri JobSpeak Index, a monthly index of white-collar hiring activity constructed from new job listings and recruiter searches on Naukri.com (Info Edge (India), 2023; Naukri.com, 2026); the foundit Insights Tracker, a monthly index of online hiring built from postings on the foundit platform (Foundit, 2024a, 2024b); Indeed's AI tracker and Hiring Lab analyses, which measure the share of postings containing AI and generative-AI keywords using a seven-day trailing average (Indeed Hiring Lab, 2024); and LinkedIn's Jobs on the Rise 2025 ranking for India, which identifies the 25 fastest-growing jobs from platform-level hiring and transition activity (LinkedIn, 2025a). The second family comprises institutional research and official documents: the WEF Future of Jobs employer surveys (World Economic Forum [WEF], 2023, 2025); the ILO's generative-AI exposure studies (Gmyrek et al., 2023; ILO, 2025); the IMF staff discussion note on AI and work (Cazzaniga et al., 2024); the OECD Employment Outlook 2023 and OECD cross-country exposure studies (OECD, 2023; Georgieff & Hye, 2021); the India Employment Report 2024 (International Labour Organization & Institute for Human Development, 2024); the Ashoka University ICPP analysis of PLFS 2018-2025 (Mahajan et al., 2026); the World Bank South Asia Development Update chapter on AI (World Bank, 2025); NASSCOM's Strategic Review (NASSCOM, 2024); RBI publications and speeches (Reserve Bank of India, 2024a; Rao, 2025); the IndiaAI Mission decision (Press Information Bureau, 2024); and employability surveys (Wheebox, 2024).

**Table 1.** *Inventory of principal secondary data sources used in the study*

| Source / dataset (publisher)                               | Type and coverage                                                                                                                          | Underlying methodology                                                                                              | Cited as                                                                                 |
|------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| Naukri JobSpeak Index (Info Edge / Naukri.com)             | Monthly white-collar hiring index; reported values used: May 2023; Feb, Jun, Jul 2025 and Feb, Jun, Jul 2026                               | Index built from new job listings and recruiter searches on Naukri.com                                              | Info Edge (India) (2023); Naukri.com (2026a, 2026b); Angel One (2026); ScanX News (2026) |
| foundit Insights Tracker (foundit, formerly Monster India) | Monthly online hiring index; December 2024 and annual 2024 editions                                                                        | Monthly analysis of job listings and hiring activity on foundit.in                                                  | Foundit (2024a, 2024b)                                                                   |
| Indeed AI Tracker / Hiring Lab analyses                    | Share of postings mentioning AI and generative-AI terms; cross-country reports 2023-2026 (nine countries; India not stated to be included) | Keyword-based classification of postings (seven-day trailing average); skill-level GenAI transformation assessments | Indeed Hiring Lab (2024, 2025a, 2025b, 2026)                                             |
| LinkedIn Jobs on the Rise 2025 (India)                     | Ranking of the 25 fastest-growing jobs in India; edition of January 2025                                                                   | Platform data on hiring and job-transition activity over the preceding three years                                  | LinkedIn (2025a, 2025b)                                                                  |

| Source / dataset (publisher)                         | Type and coverage                                                                                                                                | Underlying methodology                                                                                      | Cited as                                                        |
|------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|
| Future of Jobs Survey (World Economic Forum)         | Global employer surveys: 2023 edition (2023-2027 horizon); 2025 edition (2025-2030 horizon; 1,000+ employers, 55 economies)                      | Employer expectation surveys; occupational growth/decline projections; skills taxonomies                    | WEF (2023, 2025)                                                |
| Generative-AI exposure studies (ILO)                 | Global task-exposure indices; 2023 study and 2025 refined index (52,558 data points; 2,861 tasks)                                                | Task-level matching of occupational task lists to generative-AI automation/augmentation potential (ISCO-08) | Gmyrek et al. (2023); ILO (2025)                                |
| AI exposure analyses (IMF; OECD)                     | IMF: global AI exposure estimates (2024); OECD: cross-country exposure and employment-growth evidence (23 countries) and Employment Outlook 2023 | Occupational exposure indices adapted from Felten et al. (2021); postings-based skill-demand measures       | Cazzaniga et al. (2024); Georgieff and Hyee (2021); OECD (2023) |
| India's Jobs in Transition (ICPP, Ashoka University) | India, 2018-2025 (seven PLFS waves)                                                                                                              | Analysis of PLFS microdata with occupation-level AI-exposure mapping                                        | Mahajan et al. (2026)                                           |
| India Employment Report 2024 (ILO and IHD)           | India, 2000-2023; youth employment, education and skills                                                                                         | Compilation and analysis of PLFS and other official Indian labour statistics                                | ILO and IHD (2024)                                              |
| NASSCOM Strategic Review 2024                        | Indian technology industry, FY2024 (revenue, employment)                                                                                         | Industry surveys and member reporting                                                                       | NASSCOM (2024); Reuters (2025)                                  |
| RBI Report on Currency and Finance 2023-24           | India; digitalisation of finance                                                                                                                 | Official analytical publication of the Reserve Bank of India                                                | Reserve Bank of India (2024a)                                   |
| IndiaAI Mission decision; India Skills Report 2024   | IndiaAI: national AI programme (March 2024); ISR 2024: employability of surveyed Indian youth                                                    | Government decision documents; employability assessment surveys                                             | Press Information Bureau (2024); Wheebox (2024)                 |

For every numerical claim used in this paper, the table identifies the original source document from which the figure is taken; URLs are provided in the reference list. Where a figure is reported by a news outlet rather than the primary report (for example, the Naukri May 2025 AI/ML growth rate reported by Business Standard), the citation is to the reporting outlet and the underlying report is named. All retrieved sources were accessed and cross-checked in September 2026.

## 6.2 Methods

Given the nature of the evidence, the study employs a documented, secondary-data research design with four components, each applied only where the data support it. First, descriptive analysis: reported indicators (index levels, shares, growth rates) are tabulated and compared across sources and periods (Tables 1-2). Second, trend analysis: the Naukri JobSpeak Index's reported monthly values are plotted across 2023-2026 (Figure 1), and

reported year-on-year growth rates of AI-related hiring are compared with comparator segments (Figure 2); because trackers publish point-in-time index values rather than a continuous public time series, the figures use only the specific values reported in the cited documents, and intervals between plotted months are not uniform. Third, cross-sectional comparison: finance-related occupational groups are compared using task-based exposure estimates (ILO clerical versus professional groups), published occupational growth and decline lists (WEF 2025), and posting-share evidence (Indeed; Naukri) (Table 3). Fourth, qualitative document analysis: policy and regulatory texts (NITI Aayog, 2018; RBI, 2024a; Rao, 2025) are read for stated objectives and guard-rails concerning AI in financial services.

Skill-frequency analysis, as conventionally performed on raw posting microdata (Alekseeva et al., 2021), is not feasible here because no Indian raw job-posting microdata are publicly available at no cost; where skill frequencies are discussed, they are taken from published skill taxonomies and tracker reports (WEF, 2025; Indeed Hiring Lab, 2025b). For the same reason, and because the aggregated indicators are not mutually comparable (different platforms, index bases and reference periods), the study does not estimate regressions: any regression on, at most, a handful of reported index points would be statistically and methodologically indefensible, and its omission is a deliberate design choice consistent with the study's traceability requirement. Simple arithmetic derived by the author from two or more reported values, for example the cumulative change in the Naukri index between two reported months, is explicitly labelled as an author's calculation wherever it appears.

Finally, interpretation follows a strict separation between reported statistics and inferences. Statements of the form 'AI exposure implies job losses' are avoided by design; instead, exposure estimates, hiring signals and augmentation evidence are triangulated to characterise the direction of transformation, consistent with the augmentation-versus-automation distinction established in the ILO research (Gmyrek et al., 2023) and the heterogeneous employment effects documented by Georgieff and Hyee (2021) and the World Bank (2025).

## 7. Results

### 7.1 Trends in AI-related job demand in India (RQ1)

Reported hiring indices indicate a two-track labour market: aggregate white-collar hiring in India has been broadly stable-to-recovering, while AI-related demand has grown much faster within it. The Naukri JobSpeak Index, a monthly measure of white-collar hiring activity built from new job listings and recruiter searches on Naukri.com, stood at 2,849 in May 2023 (Info Edge (India), 2023), at 2,890 in February 2025, and at 3,233 in February 2026, a reported increase of 12 per cent year on year (Naukri.com, 2026a). The June and July 2026 editions report the index at 3,027 and 3,227, respectively, up 6 per cent and 5 per cent year on year (Naukri.com, 2026b; Angel One, 2026; ScanX News, 2026). Based on these reported values, the index is about 13.3 per cent higher in July 2026 than in May 2023 (author's calculation from reported index levels), indicating a modest aggregate expansion rather than a hiring boom.

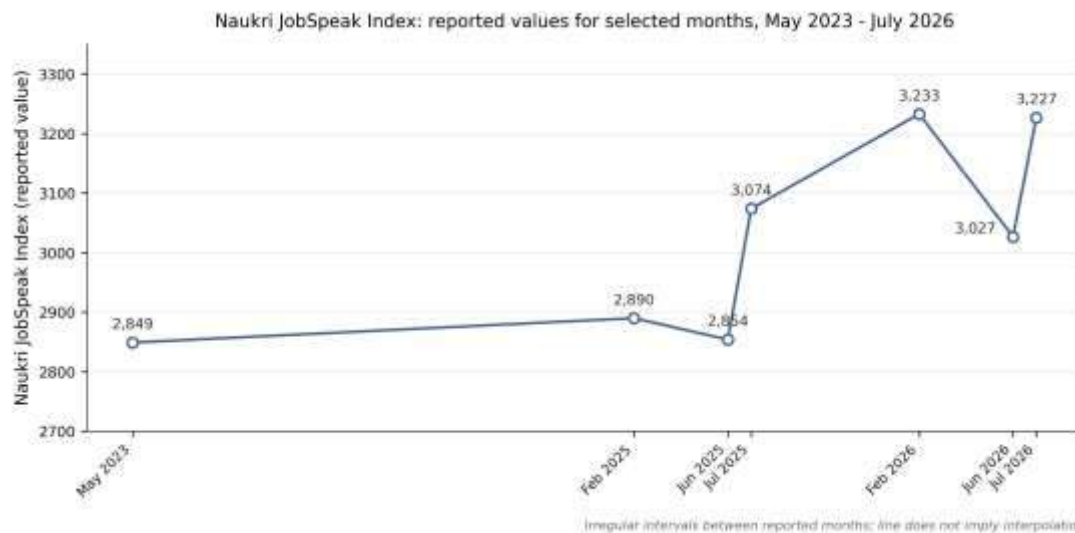


**Figure 1.** Naukri JobSpeak Index: reported values for selected months, May 2023 to July 2026. Each point is the value reported in the cited edition (Info Edge (India), 2023; Naukri.com, 2026a, 2026b; Angel One, 2026; ScanX News, 2026). Intervals between plotted months are irregular; the connecting line does not imply linear interpolation between report dates. Source: author's illustration based on reported values.

The AI-specific track is markedly stronger. The Naukri JobSpeak report for May 2025 recorded AI/ML hiring at 25 per cent year-on-year growth even as overall hiring in the information technology sector fell 5 per cent (Business Standard, 2025). In July 2026, AI and ML roles again posted the fastest growth of any segment, up 33 per cent year on year, while overall white-collar hiring rose 5 per cent (ScanX News, 2026; Angel One, 2026). The foundit Insights Tracker for December 2024 reported an overall index of 334, up 31 per cent year on year, with AI-related hiring growth of 42 per cent (Foundit, 2024a); the same tracker's annual review projected 9 per cent hiring growth for 2025, with BFSI among the leading sectors at a projected 10 per cent increase (Foundit, 2024b). Figure 2 compares these reported growth rates. In every reported period, the AI-related series outgrew the corresponding aggregate or sectoral comparator by a wide margin, and in one instance the comparator was negative.

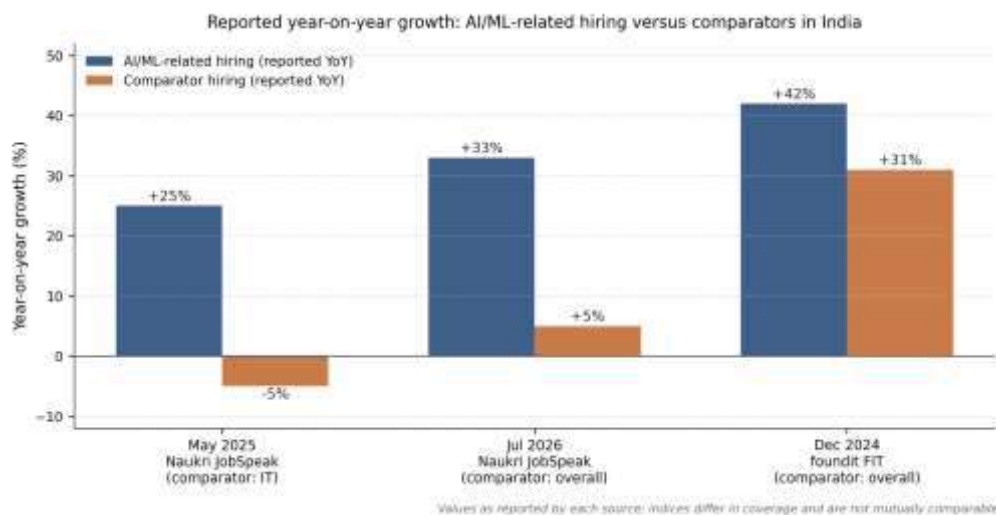


**Figure 2.** Reported year-on-year growth in AI/ML-related hiring versus comparator hiring, as published by Naukri JobSpeak (May 2025; July 2026) and the foundit Insights Tracker (December 2024). All values are as reported by the respective source; the underlying indices differ in coverage and are not mutually comparable. Source: author's illustration based on reported values (Business Standard, 2025; ScanX News, 2026; Foundit, 2024a).

Demand for AI talent is also projected to remain well ahead of supply. Deloitte's India research, released with NASSCOM, projects Indian AI talent demand to grow from about 600,000-650,000 workers in 2022 to more than 1.25 million by 2027, with AI skills supply growing at roughly 13 per cent per year against AI market demand growth of 25-35 per cent per year, and reports that 43 per cent of the Indian workforce had used AI in their organisations during the preceding year (Deloitte, 2024). TeamLease Digital estimates that the AI talent gap could reach 53 per cent by 2026 (Entrepreneur India, 2025). In platform rankings, AI Engineer is the world's fastest-growing job title on LinkedIn (LinkedIn, 2025b), and the LinkedIn Jobs on the Rise 2025 list for India includes artificial intelligence engineer among the country's fastest-growing roles (LinkedIn, 2025a). Within finance specifically, recruiting research reported by Staffing Industry Analysts (2025) projects BFSI hiring in India to grow 8.7 per cent in FY2025-26 and about 10 per cent by 2030, adding roughly 250,000 permanent roles, with more than a quarter of hiring mandates already originating beyond the eight largest metros. Table 2 consolidates these reported indicators.

**Table 2.** Selected reported indicators of AI-related hiring demand in India (all values as reported by the cited source)

| Indicator                                          | Reported value                     | Period          | Source                                        |
|----------------------------------------------------|------------------------------------|-----------------|-----------------------------------------------|
| Naukri JobSpeak Index (white-collar hiring)        | 2,849                              | May 2023        | Info Edge (India), 2023                       |
| Naukri JobSpeak Index; YoY change                  | 3,233; +12%                        | Feb 2026        | Naukri.com, 2026a                             |
| AI/ML hiring, YoY growth (Naukri)                  | +25% (IT: -5%)                     | May 2025        | Business Standard, 2025                       |
| AI/ML hiring, YoY growth (Naukri)                  | +33% (overall: +5%)                | Jul 2026        | ScanX News, 2026                              |
| foundit hiring index; AI-related hiring YoY        | 334; +31%; AI +42%                 | Dec 2024        | Foundit, 2024a                                |
| BFSI hiring projection (Adecco India research)     | +8.7% FY26; +250,000 roles by 2030 | FY2026; to 2030 | Staffing Industry Analysts, 2025              |
| Indian AI talent demand (NASSCOM-Deloitte)         | 600,000-650,000 to >1,250,000      | 2022-2027       | Deloitte, 2024                                |
| AI skills supply growth vs AI market demand growth | ~13%/yr vs 25-35% CAGR             | 2022-2027       | Deloitte, 2024                                |
| Indian workforce that used AI in past year         | 43%                                | 2024            | Deloitte, 2024                                |
| Projected AI talent gap (TeamLease Digital)        | 53%                                | by 2026         | Entrepreneur India, 2025                      |
| AI Engineer rank in LinkedIn fastest-growing jobs  | #1 (global)                        | Jan 2025        | LinkedIn, 2025b                               |
| Overall youth employability (India Skills Report)  | 51.25% (vs 40.44% in 2017)         | 2024            | Wheebox, 2024; Press Information Bureau, 2025 |

## 7.2 Changing AI and digital skill requirements (RQ2)

The skills evidence points to a broadening of required competencies rather than wholesale skill replacement. Globally, the WEF (2025) employer survey finds that nearly two-fifths (39 per cent) of workers' key skills are expected to change by 2030, that 63 per cent of employers identify the skills gap as the principal barrier to transformation, and that, on average, 59 of every 100 workers will require reskilling or upskilling by 2030, with 11 of them unlikely to receive it. Technology skills in AI, big data, networks and cybersecurity show the fastest projected growth in demand, but human skills, analytical thinking, creative thinking, resilience, flexibility, agility

and collaboration, remain core (WEF, 2025). In the same survey, 77 per cent of employers plan to upskill workers and about half plan to reorient their business in response to AI, while 41 per cent plan to reduce their workforce where AI can automate tasks, a figure that signals both transformation pressure and widespread complementary investment (WEF, 2025).

Posting-based analyses qualify these projections. Indeed's AI at Work research assesses that about 26 per cent of posted jobs could be highly transformed by generative AI and 54 per cent moderately so, that almost half (46 per cent) of the skills in a typical posting are poised for 'hybrid transformation', in which human oversight remains critical, and that, of more than 2,800 work skills assessed, none was found to be very likely to be replaced by generative AI (Indeed Hiring Lab, 2025b). For India's finance talent pipeline, however, supply-side indicators remain weak: overall youth employability was 51.25 per cent in the India Skills Report 2024, up from 40.44 per cent in 2017 (Wheebox, 2024; Press Information Bureau, 2025), and only about 60 per cent of Indian workers and 71 per cent of Gen-Z workers recognise that acquiring AI skills can enhance their career prospects, although two of three Indians report plans to learn at least one digital skill, with AI and machine learning at the top of the list (Deloitte, 2024). The combination of rapid skill-demand change (WEF, 2025), hybrid rather than replacement skill transformation (Indeed Hiring Lab, 2025b) and only moderate employability (Wheebox, 2024) implies that skill requirements in Indian finance are shifting toward bundles that pair financial-domain knowledge with AI literacy, data competence and human-interaction strengths.

### **7.3 Differences across banking, accounting, insurance, investment and FinTech (RQ3)**

The evidence base, while not permitting a single India-specific exposure index for finance occupations, is consistent in its cross-occupational ordering. At the automation-exposed end, the ILO finds that clerical work is the only major occupational group highly exposed to generative AI, with 24 per cent of clerical tasks in the high-exposure category and a further 58 per cent at medium exposure, against 1-4 per cent high exposure for professional groups (Gmyrek et al., 2023). Bank tellers and related clerks, cashiers and ticket clerks, administrative assistants and data-entry-type roles appear among the fastest-declining occupations in the WEF (2025) projections, and accountants and auditors are likewise listed among roles expected to contract by 2030. Yet even here, the posting-share evidence suggests adaptation rather than disappearance: generative AI is still rarely mentioned in white-collar postings, including accounting, despite substantial capability overlap (Indeed Hiring Lab, 2025a), and BFSI hiring in India continues to expand with demand for frontline, digital and compliance functions (Staffing Industry Analysts, 2025).

Insurance presents a distinctive pattern: Indeed's cross-country analysis places insurance among the sectors where generative-AI mentions in postings fall short of expectations (Indeed Hiring Lab, 2024), while Naukri's JobSpeak reports identify insurance as one of the sectors leading hiring growth alongside AI/ML roles (Naukri.com, 2026b). This combination, strong volume hiring with low explicit AI content in postings, is consistent with an industry in the early phase of AI absorption, and one whose agency distribution channel remains large: the Insurance Regulatory and Development Authority of India reports an insurance agent base of about 5.44 million (54.4 lakh) in FY2024-25 (IRDAI, 2025; ETBFSI, 2026). Investment-related professional work (research, analysis, portfolio support) falls in the augmentation-dominant zone of the exposure literature: professional groups show low high-exposure task shares (Gmyrek et al., 2023), and LLM exposure is concentrated in higher-wage cognitive occupations where complementary software, not the model alone, drives most of the potential effect (Eloundou et al., 2024). FinTech sits at the expansion pole: fintech engineers are among the fastest-growing roles projected globally to 2030 (WEF, 2025), and India's FinTech ecosystem, estimated by the India Brand Equity Foundation

(IBEF) at about USD 150 billion in market size by 2025 and the third largest globally, generates demand for hybrid finance-technology skill sets (IBEF, 2025). Table 3 summarises this cross-occupational mapping.

**Table 3.** Evidence mapping of AI-related transformation across finance-related occupational groups

| Occupational group                                                              | Key evidence (reported)                                                                                                                                                                                                                                                             | Source(s)                                                                      |
|---------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
| Banking: tellers, clerks, transaction processing                                | Clerical work is the only occupational group highly exposed to generative AI (24% of tasks highly exposed; 58% medium); bank tellers and related clerks listed among fastest-declining roles to 2030; BFSI hiring nonetheless growing with frontline, digital and compliance demand | Gmyrek et al. (2023); WEF (2025); Staffing Industry Analysts (2025)            |
| Accounting and bookkeeping                                                      | Accountants and auditors among roles projected to decline fastest by 2030; generative AI still rarely mentioned in accounting postings despite capability overlap; no assessed skill very likely to be fully replaced                                                               | WEF (2025); Indeed Hiring Lab (2025a, 2025b)                                   |
| Insurance                                                                       | Insurance among sectors where generative-AI posting mentions fall short of expectations globally; insurance simultaneously among sectors leading Indian hiring growth alongside AI/ML; agent base about 5.44 million in FY2024-25                                                   | Indeed Hiring Lab (2024); Naukri.com (2026b); IRDAI (2025); ETBFSI (2026)      |
| Investment and market intermediaries (research, analysis, portfolio operations) | Professional groups show 1-4% high-exposure task shares; LLM exposure concentrated in higher-wage cognitive work and largely conditional on complementary software; dominant effect augmentation                                                                                    | Gmyrek et al. (2023); Eloundou et al. (2024); Cazzaniga et al. (2024)          |
| FinTech and finance-technology engineering                                      | Fintech engineers among the fastest-growing roles globally to 2030; India's FinTech ecosystem about USD 150 billion by 2025, third largest globally; IndiaAI Mission supports AI skills pipeline                                                                                    | WEF (2025); IBEF (2025); Press Information Bureau (2024)                       |
| AI/data specialist roles within finance                                         | AI/ML hiring growth of +25% (May 2025) and +33% (Jul 2026) on Naukri; AI-related hiring +42% YoY on foundit (Dec 2024); AI Engineer #1 globally on LinkedIn                                                                                                                         | Business Standard (2025); ScanX News (2026); Foundit (2024a); LinkedIn (2025b) |

#### 7.4 Emerging and declining skill requirements (RQ2 continued)

Triangulating the sources yields a consistent picture of skill churn within finance (Table 4). Emerging requirements centre on AI and big-data competence, cybersecurity awareness, technological literacy, and the human skills that complement them: creative thinking, resilience, flexibility, curiosity and lifelong learning (WEF, 2025); hybrid human-AI working skills, since nearly half of posting skills are slated for transformation in which human oversight remains essential (Indeed Hiring Lab, 2025b); and social-interaction skills, whose labour-market premium is long established (Deming, 2017). Declining requirements attach to routine information-processing tasks: manual data entry, basic transaction handling, standardised document processing and routine bookkeeping, the task content most exposed in the ILO's clerical category (Gmyrek et al., 2023) and embodied in the occupations the WEF (2025) projects to decline. Two caveats are important. First, occupational decline lists describe net projected changes in demand for roles, not the disappearance of skills from all contexts; Indeed's assessment that none of more than 2,800 skills is very likely to be fully replaced indicates recombination rather than erasure of skill content (Indeed Hiring Lab, 2025b). Second, declining lists are global employer expectations rather than India-specific forecasts; in

India's BFSI segment, hiring for several of these occupational categories continues to grow in absolute terms (Staffing Industry Analysts, 2025), implying that the transformation currently operates more through changing job content than through net contraction.

**Table 4.** Emerging versus declining skill requirements in AI-era finance work (evidence-based, with sources)

| Direction | Skills / task content (evidence)                                                                                                                                                                                                                                  | Source(s)                                                    |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------|
| Emerging  | AI and big-data competence; networks and cybersecurity; technological literacy; fintech engineering and AI/ML specialisation (fastest-growing demand to 2030)                                                                                                     | WEF (2025); LinkedIn (2025b)                                 |
| Emerging  | Hybrid human-AI working skills with human oversight (46% of posting skills poised for hybrid transformation); validation and supervision of AI outputs                                                                                                            | Indeed Hiring Lab (2025b)                                    |
| Emerging  | Creative thinking, resilience, flexibility, agility, curiosity and lifelong learning; analytical thinking; collaboration; social-interaction skills carrying a long-run premium                                                                                   | WEF (2025); Deming (2017)                                    |
| Declining | Routine information processing: data entry, posting and service clerks, cashiers and ticket clerks, administrative assistants and executive secretaries, bank tellers and related clerks, accountants and auditors (net role demand projected to decline by 2030) | WEF (2025)                                                   |
| Declining | Clerical task content: 24% of clerical tasks highly exposed and 58% medium-exposed to generative AI; niche content work (e.g., online freelance writing, translation) already contracting in South Asia                                                           | Gmyrek et al. (2023); World Bank (2025)                      |
| Caveat    | None of 2,800+ assessed skills is very likely to be replaced by generative AI; decline lists describe net role demand, not skill erasure; Indian BFSI continues to hire several listed occupations in absolute terms                                              | Indeed Hiring Lab (2025b); Staffing Industry Analysts (2025) |

## 8. Discussion

The Indian evidence read against the international literature supports a transformation-centred interpretation. In the task-based framework, AI reallocates the task content of finance work among substitution, augmentation and reinstatement (Acemoglu & Restrepo, 2019). The strongest experimental and quasi-experimental evidence to date finds augmentation as the modal outcome: a generative-AI assistant raised the productivity of about 5,200 customer-support agents by 15 per cent on average, with the largest gains for the least experienced (Brynjolfsson et al., 2025), and ChatGPT raised the quality of professional writing output by 18 per cent while reducing time taken by 40 per cent (Noy & Zhang, 2023). The ILO's task-level index reaches the same conclusion globally: even in the most exposed group, clerical work, the predominant potential effect is augmenting tasks within occupations rather than automating occupations wholesale (Gmyrek et al., 2023). India's hiring signals are consistent with this: aggregate white-collar indices rise modestly while AI-related segments grow at 25-42 per cent per year (Business Standard, 2025; Foundit, 2024a; ScanX News, 2026), and BFSI hiring expands with a changed functional mix toward digital, frontline and compliance roles (Staffing Industry Analysts, 2025).

At the same time, the displacement end of the distribution is real and identifiable. The WEF (2025) projects declines for bank tellers and related clerks, cashiers, administrative assistants, data-entry roles, and accountants and auditors; the ILO places clerical work alone in the high-exposure category (Gmyrek et al., 2023); and the World Bank (2025) documents measurable employment reductions in specific, highly exposed niches in South Asia, such as online freelance writing and translation. These are precisely the routine information-processing task bundles that

AI performs best (Brynjolfsson & Mitchell, 2017). The critical analytical point, however, is that exposure is not destiny: across 23 OECD countries, Georgieff and Hyee (2021) find no clear relationship between AI exposure and employment growth, and, if anything, higher employment growth in high-computer-use occupations with greater AI exposure; the OECD (2023) similarly finds no signs of slowing labour demand in the most automation-prone occupations since the rise of machine learning. The IMF estimates that almost 40 per cent of global employment is exposed to AI, with exposure shares of about 60 per cent of employment in advanced economies, 40 per cent in emerging markets and 26 per cent in low-income countries, and emphasises that exposure may complement or substitute for workers depending on task composition and complementary investment (Cazzaniga et al., 2024).

India's own economy-wide evidence adds a distributional nuance that matters for finance. Using PLFS microdata for 2018-2025, Mahajan et al. (2026) document job polarisation: nearly half of the increase in non-farm wage employment came from the least AI-exposed fifth of occupations, medium-exposed occupations barely grew, and high-skilled cognitive occupations, though most AI-exposed, continued to add jobs. Translated to finance, this suggests a barbell: continued expansion of high-skill AI-complementary professional roles (fintech engineering, AI/data specialisation, model governance) alongside continued growth of in-person, trust-intensive frontline roles, with the middle of the distribution, routine processing and mid-level clerical work, squeezed hardest. The reported wage pattern in the same study, real wages of technicians and associate professionals falling by about 20 per cent over 2018-2025 while those of professionals gained about 22.6 per cent, reinforces the skill-biased character of the ongoing shift (Mahajan et al., 2026).

Two further interpretive points follow. First, the low explicit generative-AI content of Indian finance postings, paralleling Indeed's finding that accounting and other white-collar postings rarely mention generative AI despite capability overlap (Indeed Hiring Lab, 2025a), implies that posting language currently understates AI's penetration of finance work; skill demand is transforming inside job roles faster than job titles and posting vocabulary change. Second, regulatory posture matters for the pace and direction of change in Indian finance. The RBI's senior leadership has framed AI as potentially transformative for credit access and banking efficiency while insisting on responsible, governed adoption (Rao, 2025; Rabi Sankar, 2025), and the RBI's own analysis documents the digitalisation of Indian finance, including a 48.5 per cent share of global real-time payments (Reserve Bank of India, 2024a), that constitutes the data substrate on which AI applications in banking are being built. Taken together, the evidence supports neither a doom-laden nor a complacent reading: finance employment in India is being re-composed, with strong growth at the AI frontier, persistent demand at the human-interaction frontier, and genuine pressure on routine processing roles.

## 9. Implications

### 9.1 Implications for finance professionals

For individuals, the evidence implies investing in hybridisation rather than resistance. Because augmentation is the modal effect documented in credible studies (Brynjolfsson et al., 2025; Noy & Zhang, 2023; Gmyrek et al., 2023), the returns to AI literacy, data competence and the ability to supervise, validate and interrogate AI outputs are likely to exceed the returns to narrowly specialising in tasks that AI performs well. The WEF's projection that 59 of every 100 workers will need reskilling by 2030, and that nearly two-fifths of skills will change over the same horizon (WEF, 2025), converts continuous learning from a slogan into a balance-sheet necessity for finance careers. Simultaneously, the long-run premium on social-interaction skills (Deming, 2017) and the continued growth of trust-intensive frontline and compliance functions in BFSI hiring (Staffing Industry Analysts, 2025) indicate that

relationship management, ethical judgement and communication will remain scarce, rewarded complements to technical capability. Professionals in the most exposed niches, routine accounting operations, transaction processing and back-office clerical work, should prioritise migration toward the expanding poles identified in Section 7, including fintech engineering, AI-assisted advisory, model risk and data governance.

## 9.2 Implications for higher education

Higher education faces a demonstrable capability gap. Overall youth employability in India stood at 51.25 per cent in 2024 (Wheebox, 2024), AI talent demand is projected to more than double by 2027 (Deloitte, 2024), and the AI talent gap could reach 53 per cent by 2026 (Entrepreneur India, 2025). Curricula in commerce, accounting and finance should therefore integrate applied AI and data analytics, not as electives but as core content, while preserving the domain depth in accounting standards, financial regulation and risk that constitutes India's comparative advantage in financial services. Three specific directions follow from the evidence. First, programmes should teach hybrid human-AI workflows, reflecting the finding that 46 per cent of posting skills are slated for hybrid transformation with human oversight central (Indeed Hiring Lab, 2025b). Second, assessment should move toward the evaluation of judgement and communication, the skills that AI complements most and that employers rank among core requirements (WEF, 2025). Third, institutions should align with national skilling infrastructure, including the IndiaAI FutureSkills pillar of the IndiaAI Mission (Press Information Bureau, 2024) and the skilling priorities of the National Strategy for Artificial Intelligence (NITI Aayog, 2018), to avoid duplicating content and to leverage shared compute and dataset platforms.

## 9.3 Implications for policy

For policymakers, three priorities emerge from the evidence. First, scale reskilling intensity: with AI skills supply growing at about 13 per cent annually against demand growth of 25-35 per cent (Deloitte, 2024), the IndiaAI Mission's compute and FutureSkills investments (Press Information Bureau, 2024) should be matched by sector-specific programmes for BFSI workforce transitions. Second, attend to distribution: the ILO warns that generative-AI exposure is gendered because clerical work is an important source of female employment (Gmyrek et al., 2023), and India's own employment reporting shows youth bearing a disproportionate share of unemployment (International Labour Organization & Institute for Human Development, 2024); transition support should therefore be targeted rather than generic. Third, improve measurement: this study's central practical constraint was the absence of a public, harmonised Indian job-posting microdata resource; official publication of anonymised posting microdata, or systematic integration of tracker indices with PLFS outcomes, would materially raise the quality of future evidence on AI and labour demand, an agenda consistent with the monitoring approaches of the International Labour Organization (2025) and the OECD (2023).

## 10. Limitations

The study's design choices impose five limitations that readers should weigh alongside its findings. First, all quantitative inputs are secondary aggregates published by trackers, multilateral bodies and firms; no raw job-posting microdata for India were analysed, because none are publicly available at no cost; consequently, no original skill-frequency analysis on raw postings, and no regressions, were performed, and the reported statistics should not be assumed independent of one another. Second, the underlying indices are not mutually comparable: Naukri JobSpeak measures white-collar hiring activity on one platform, the foundit tracker reflects a different posting universe, and Indeed's AI-posting analyses cover a set of nine countries that is not stated to include India, so cross-

source comparisons are directional rather than exact, and the figures plotted here use irregular intervals between reported months. Third, postings measure gross hiring demand, not net employment; they exclude internal mobility, suppressed hiring and separations, so posting trends can coexist with either net headcount decline or growth. Fourth, several inputs are expectations rather than outcomes, notably the WEF employer projections and the task-exposure indices, which measure potential effects; the cross-country literature reviewed above shows that potential exposure does not translate mechanically into employment change (Georgieff & Hyee, 2021; OECD, 2023). Fifth, the India-specific finance-sector evidence base is young; the most relevant economy-wide study (Mahajan et al., 2026) covers the whole labour market, and sector-level inference here therefore relies on triangulation across sources of differing vintage, with all sources accessed by September 2026. These limitations argue for, rather than against, continued measurement; they do not, in our assessment, overturn the qualitative conclusions, which rest on the consistency of multiple independent sources.

## 11. Conclusion

This study set out to establish, from genuinely public and traceable secondary data, how artificial intelligence is transforming finance jobs in India. On the level of demand (RQ1), the reported evidence is unambiguous in direction: AI-related hiring grew by 25-42 per cent year on year in reported periods between 2024 and 2026, against modest aggregate white-collar growth, and AI talent demand is projected to more than double between 2022 and 2027. On skill content (RQ2), the weight of evidence indicates hybrid transformation: nearly two-fifths of skills are expected to change by 2030, almost half of posting skills are poised for hybrid transformation with human oversight, and no assessed skill is very likely to be fully replaced, a pattern consistent with augmentation rather than wholesale substitution. Across occupations (RQ3), exposure is sharply uneven: routine clerical, teller, data-entry and bookkeeping tasks sit at the exposed end; fintech engineering, AI/data specialisation and compliance-oriented functions at the expanding end; and insurance displays high hiring volumes with low explicit AI content, suggesting early-phase absorption.

The central conclusion is that India's finance employment is being re-composed rather than eliminated. The empirical record shows simultaneous expansion at the AI frontier, persistence at the human-interaction frontier, and pressure on routine processing in the middle, a barbell that matches the task-based theory of technological change and the emerging Indian evidence on job polarisation (Mahajan et al., 2026). Exposure to AI is therefore best understood as a transformation pressure whose final incidence depends on complementary skills, institutional adaptation and policy, not as a deterministic job-loss forecast. For finance professionals, the implication is to hybridise; for higher education, to embed AI and data competence in finance curricula while deepening domain and human-interaction strengths; and for policy, to scale targeted reskilling and to build public labour-market measurement infrastructure. Future research should exploit linked posting-survey-administrative microdata as they become available, apply occupational exposure indices to Indian finance specifically, and track whether the augmentation-dominant pattern documented here persists as adoption deepens.

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