



**BALANCING EFFICIENCY AND ETHICS: AI AND ESG GOVERNANCE IN KERALA'S  
IT SECTOR**

<sup>1</sup>Anna Anit P V

Research Scholar,

JAIN (Deemed to be University, Kochi, a.anna@jainuniversity.ac.in, 8891227519

<sup>2</sup>Dr. Asha A G

Assistant Professor, JAIN, Deemed to be University, Kochi

<https://doi.org/10.5281/zenodo.23364751>

**Abstract**

The diffusion of generative and predictive artificial intelligence (AI) across knowledge-intensive services is reshaping the organisation of work and placing new demands on corporate governance. This paper presents an integrative review of the literature at the intersection of AI-driven task transformation, stakeholder theory, and Environmental, Social, and Governance (ESG) practice, and applies it to the export-oriented information technology (IT) sector of Kerala, India. Drawing on scholarly evidence on occupational exposure, augmentation and automation, algorithmic management, and AI ethics, together with multilateral benchmark reports and park-level administrative data from Kerala's state-backed technology parks, the review reaches three principal conclusions. First, the literature converges on a task-based view in which exposure is concentrated in routine cognitive work, while outcomes depend on whether AI is deployed to augment or to substitute labour. Second, ESG scholarship remains largely disclosure-oriented and rarely examines the workforce consequences of AI, even though the Social and Governance pillars offer a natural structure for oversight. Third, regional evidence shows export revenues outpacing direct employment growth (7.97% versus 5.50% over 2023–25; 76.6% versus 51.7% for Technopark over 2016–25). This divergence is consistent with productivity-led task automation, though it cannot establish it on its own. Drawing these strands together, the review proposes a five-stage conceptual model (Identify, Augment, Reskill, Govern, Measure) and a five-domain Governance Engine of indicators, and sets out propositions and a research agenda for empirical validation.

**Keywords:** *AI, ESG governance, Workforce transformation, algorithmic management, Kerala IT sector*

**1. Introduction**

**1.1 Background**

Artificial intelligence (AI) has moved from the periphery of enterprise technology to the centre of how knowledge work is organised. Earlier waves of automation displaced routine manual and clerical tasks that



could be expressed as explicit rules (Autor et al., 2003; Autor, 2015). Contemporary machine-learning systems, and generative models in particular, are able to perform non-routine cognitive tasks such as code synthesis, software testing, technical writing, and analytical summarisation (Brynjolfsson & McAfee, 2014; Eloundou et al., 2024). Estimates of exposure are substantial: the International Monetary Fund (IMF) projects that almost 40% of employment worldwide is exposed to AI (Cazzaniga et al., 2024), and the World Economic Forum (WEF) expects 39% of core worker skills to change by 2030 (WEF, 2025).

These developments are especially consequential for export-oriented information technology (IT) and IT-enabled services (ITeS). The Indian software services model was built on a large pool of skilled engineering labour deployed at relatively low cost (Arora et al., 2001), and in that model revenue growth has historically been tied to billable headcount. Where cognitive automation weakens the link between headcount and output, firms face decisions about retention, retraining, monitoring, and recruitment whose consequences fall directly on employees.

## **1.2 The governance question**

How AI is introduced is not only a technical or financial decision. It shapes who is retained, retrained, monitored, or screened out, and so raises questions of stakeholder obligation and corporate governance (Freeman, 1984; Donaldson & Preston, 1995). Environmental, Social, and Governance (ESG) frameworks, designed mainly to give investors and regulators non-financial disclosures, are increasingly expected to address such questions. However, the ESG literature has focused largely on the financial relevance and measurement of ESG performance (Gillan et al., 2021) and on the divergence of ratings across providers (Berg et al., 2022). It has paid little attention to the workforce consequences of AI. This paper argues that the Social (S) and Governance (G) pillars are better understood as an upstream architecture for managing technological transition than as a downstream reporting layer.

## **1.3 Regional context and research gap**

Kerala offers a distinctive setting in which to examine this argument. Kerala pairs high educational attainment and strong social development indicators with a network of state-promoted technology parks: Technopark in Thiruvananthapuram, Infopark in Kochi, and Cyberpark in Kozhikode. These parks are embedded in global software supply chains (Kerala State Planning Board, 2026; Software Technology Parks of India [STPI], 2025). By contrast, the most influential empirical work on AI exposure and labour-market effects draws largely on United States data (Acemoglu & Restrepo, 2020; Felten et al., 2021; Eloundou et al., 2024). To the authors' knowledge, integrated evidence on how cognitive-AI exposure and governance challenges play out in a regional, highly educated, export-dependent IT ecosystem in an emerging economy remains scarce.



#### ***1.4 Objectives, research questions, and contribution***

The review pursues four objectives: (i) to synthesise the literature on AI, task transformation, augmentation, and employment; (ii) to examine how ESG and stakeholder scholarship can inform the governance of AI-driven workforce transitions; (iii) to assess descriptive evidence from Kerala's IT parks; and (iv) to develop a conceptual framework and research agenda. Three research questions guide the analysis:

- **RQ1.** What does the literature establish about the effects of AI on task composition, productivity, and employment in knowledge-intensive services?
- **RQ2.** How can ESG governance, and the Social and Governance pillars in particular, be conceptualised to oversee AI-driven workforce transitions?
- **RQ3.** What does descriptive evidence from Kerala's IT parks indicate about export–employment dynamics, and what governance implications follow?

The paper contributes by connecting three literatures that are usually treated separately—task-based labour economics, stakeholder and ESG scholarship, and research on algorithmic management and AI ethics—and by grounding the resulting synthesis in regional evidence. Section 2 outlines the review approach. Section 3 sets out the theoretical foundations. Section 4 reviews evidence on AI, tasks, and labour markets, and Section 5 examines the social risks of workplace AI. Section 6 turns to the Indian and Kerala context and presents descriptive evidence. Section 7 synthesises themes and gaps, Section 8 develops the conceptual framework, Section 9 discusses implications, Section 10 sets out limitations and a research agenda, and Section 11 concludes.

## **2. Review Approach**

This paper adopts an integrative narrative review design. Integrative reviews synthesise diverse bodies of work in order to generate conceptual framings and identify gaps, rather than to aggregate effect sizes across a homogeneous set of studies (Snyder, 2019). This design suits the topic, which spans labour economics, management, corporate governance, and technology ethics, and for which regional evidence sits largely in administrative and institutional sources.

The evidence base was assembled purposively across four streams: (a) the task-based labour economics of automation and AI; (b) stakeholder theory and ESG scholarship; (c) research on algorithmic management, hiring bias, and AI ethics; and (d) institutional reports and administrative data on the Indian and Kerala IT sector. Peer-reviewed sources were prioritised for conceptual and empirical claims. Multilateral and government reports were used for benchmark projections and regional statistics, where academic sources are limited. The sources were synthesised thematically, and the regional secondary data were analysed descriptively using simple growth rates. Because the review is purposive rather than systematic, it makes no claim to exhaustive coverage; section 10 discusses the implications of this design.



### **3. Theoretical Foundations**

#### **3.1 Stakeholder theory and the ethics of technological transition**

Stakeholder theory holds that the purpose of the firm extends beyond shareholder wealth to the interests of all who affect or are affected by its activities, including employees, suppliers, communities, and regulators (Freeman, 1984). Donaldson and Preston (1995) distinguish three complementary justifications: a descriptive account of how firms actually relate to their stakeholders, an instrumental account linking stakeholder management to firm performance, and a normative account grounded in stakeholders' intrinsic moral standing. Applied to AI, the normative strand implies that employees are entitled to fair treatment when transitions alter or eliminate their tasks. The instrumental strand suggests that retention, trust, and skill preservation underpin long-term organisational resilience.

This framing changes how workforce reduction should be read. Automation-driven headcount cuts are no longer an immediate efficiency gain; they become a decision to be weighed against implicit employment commitments, the loss of firm-specific human capital, and reputational and regulatory risk. Stakeholder-centric governance therefore treats labour retention, continuous skills development, and algorithmic fairness as operational imperatives rather than discretionary philanthropy.

#### **3.2 ESG: from disclosure to architecture**

ESG frameworks originated primarily as mechanisms for non-financial disclosure and capital allocation. Reviews of the corporate-finance literature point to persistent questions about how ESG performance should be measured and through what mechanisms it affects firm outcomes (Gillan et al., 2021). Ratings from different providers also diverge substantially, largely because of differences in measurement and scope (Berg et al., 2022). Together, these findings suggest that ESG scores alone are an unreliable basis for governing a specific and fast-moving risk such as AI-driven workforce change.

An architectural conception of ESG responds to this limitation. It embeds ethical and human-centric constraints directly into technology selection, system design, and workflow deployment, so that the Social and Governance pillars act upstream of deployment decisions rather than after them. Three operational dimensions define this architecture:

- **Algorithmic oversight:** internal control frameworks for automated recruitment, performance scoring, and task-allocation systems, with the auditability and validation expected of financial reporting systems.
- **Operational transparency:** clear communication to employees about where, how, and to what extent automated cognitive systems are used in daily workflows, including human escalation paths.



- **Demographic bias mitigation:** continuous, documented audits of proprietary and third-party AI tools to detect and remedy disparate impacts across gender, age, and other groups in hiring, evaluation, and promotion.

### **3.3 AI ethics principles as governance content**

A parallel literature on AI ethics supplies the normative content that such an architecture requires. A mapping of 84 ethics guidelines found convergence around five principles (transparency, justice and fairness, non-maleficence, responsibility, and privacy), although interpretations and implementation strategies differ (Jobin et al., 2019). The AI4People framework similarly proposes beneficence, non-maleficence, autonomy, justice, and explicability as the ethical foundation for a good AI society (Floridi et al., 2018).

At the intergovernmental level, the UNESCO (2021) Recommendation on the Ethics of Artificial Intelligence emphasises human oversight and determination, transparency, fairness, and privacy, and India's national approach document sets out principles for responsible AI (NITI Aayog, 2021). The challenge lies in translating these principles into enforceable organisational practice, which is precisely where ESG governance instruments—scorecards, audits, disclosure, and board oversight—can contribute.

## **4. AI, Tasks, and Labour Markets: What the Evidence Shows**

### **4.1 From routine-based change to AI exposure**

The task-based approach to technological change holds that technologies substitute for and complement labour at the task level rather than at the occupation level. Computerisation historically displaced routine tasks that can be expressed as explicit rules, while complementing non-routine analytical and interactive work (Autor et al., 2003; Autor, 2015). Occupation-level projections, most prominently the estimate by Frey and Osborne (2017) that 47% of US employment was at high risk of computerisation, drew attention to the breadth of potential exposure, although such headline figures are better read as indications of technical feasibility than as forecasts of job loss.

Generative AI alters the boundary of exposure. Felten et al. (2021) construct an AI occupational exposure measure by linking advances in AI application areas to the abilities that occupations require, and show that exposure is not confined to low-skill work. Eloundou et al. (2024) estimate that around 80% of the US workforce could have at least 10% of its tasks affected by large language models and around 19% could have at least half of their tasks affected, with higher-income occupations facing greater exposure. Neither study equates exposure with displacement. Exposure signals a potential for change, and whether that change takes the form of substitution or complementarity depends on how the technology is deployed.



The net employment effect depends on the balance between competing forces. Acemoglu and Restrepo (2018) distinguish three: a displacement effect, as tasks are reallocated from labour to machines; a productivity effect, as lower costs raise demand for labour in non-automated tasks; and a reinstatement effect, as new labour-intensive tasks are created.

Evidence from industrial robots in US local labour markets shows negative employment and wage effects where adoption is concentrated (Acemoglu & Restrepo, 2020), underscoring that favourable outcomes are not automatic. Brynjolfsson and McAfee (2014) similarly argue that the distribution of gains from digital technologies depends on the choices that societies and organisations make.

#### **4.2 Augmentation and automation**

Raisch and Krakowski (2021) argue that automation and augmentation are interdependent rather than alternatives: substituting machines for human tasks changes what remains for people to do, and augmenting people alters what can subsequently be automated. Managerial choices about which mode to emphasise therefore have consequences for skills, discretion, and job quality.

Early empirical evidence on productivity is encouraging. In a large field study of customer-support agents, access to a generative AI assistant raised productivity by about 14% on average and by about 34% for novice and low-skilled workers, with minimal effects for the most experienced (Brynjolfsson et al., 2023). In an online experiment on professional writing tasks, access to ChatGPT reduced completion time by about 40% and raised output quality by about 18%, while narrowing differences between workers (Noy & Zhang, 2023). These findings suggest that augmentation can compress performance gaps. They also raise a question of particular relevance to IT services: if AI assistance takes over the entry-level tasks through which novices traditionally build expertise, how will future senior talent be developed? The literature has yet to answer this question, and it motivates the emphasis on reskilling and internal mobility in the framework proposed in Section 8.

#### **4.3 Multilateral benchmarks**

Multilateral institutions have translated these micro-level insights into cross-national projections and normative guidance (Table 1). Two features of these benchmarks matter for the present review. First, they measure exposure and potential rather than realised displacement, and their estimates are sensitive to method. Second, they point to an unequal global distribution: exposure is highest in economies with more digitised occupational structures, and emerging economies sit between advanced and low-income economies (Cazzaniga et al., 2024). The IMF also constructs an AI preparedness index combining digital infrastructure, human capital and labour-market policies, innovation, and regulation—dimensions on which regional ecosystems differ and on which public policy can act (Cazzaniga et al., 2024).



**Table 1.** *Multilateral benchmarks on AI, work, and governance*

| Source                       | Scope                                      | Key finding or position                                                                                                                                                                                                                                                 |
|------------------------------|--------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Cazzaniga et al. (2024), IMF | Global employment exposure                 | About 40% of global employment is exposed to AI: roughly 60% in advanced economies, 40% in emerging markets, and 26% in low-income countries. In advanced economies, about half of exposed jobs may benefit from AI integration, while the rest face displacement risk. |
| WEF (2025)                   | Global skills and jobs to 2030             | 39% of core worker skills are expected to change by 2030; 170 million new roles are projected against 92 million displaced, a net gain of 78 million.                                                                                                                   |
| Gmyrek et al. (2023), ILO    | Generative AI and job quality and quantity | Generative AI is more likely to augment than to eliminate occupations, with clerical work most exposed; outcomes depend on how technology is implemented and on policy choices.                                                                                         |
| OECD (2023)                  | AI and the labour market                   | High-skilled white-collar occupations are among the most exposed to recent AI advances; stresses policy action on training, worker consultation, and workplace use of AI.                                                                                               |
| UNESCO (2021)                | Ethics of AI (normative)                   | Establishes principles including human oversight, fairness and non-discrimination, transparency, and privacy, with safeguards against harmful surveillance.                                                                                                             |

*Note.* IMF = International Monetary Fund; WEF = World Economic Forum; ILO = International Labour Organisation; OECD = Organisation for Economic Co-operation and Development.



## **5. Social Risks of Workplace AI**

### ***5.1 Efficiency gains and their limits***

Controlled and field evidence indicates that generative AI can raise productivity in writing and customer-support tasks (Brynjolfsson et al., 2023; Noy & Zhang, 2023). Software engineering, enterprise analytics, and cybersecurity are widely seen as domains where similar gains are plausible. Realising such gains at organisational scale, however, depends on complementary investments in skills, process redesign, and governance. Without these investments, efficiency gains may coexist with the social costs that ESG frameworks are meant to surface.

### ***5.2 A triad of social risks***

Occupational displacement and task erosion. Routine cognitive tasks (manual software testing, elementary code maintenance, data entry, and standardised reporting) are the most plausible candidates for substitution (Autor et al., 2003; Acemoglu & Restrepo, 2018). Without proactive reskilling, workers concentrated in such entry-level functions risk task erosion and career stagnation, even if aggregate employment continues to grow. Work intensification and algorithmic management. When AI-assisted output becomes the new performance baseline, productivity gains can be converted into higher quotas and compressed timelines rather than into time for learning or discretion. Research on algorithmic management shows that digital systems increasingly perform managerial functions (directing, evaluating, and disciplining workers), often with limited transparency and with implications for autonomy and control (Kellogg et al., 2020). Continuous monitoring, automated performance scoring, and attention tracking can erode trust. This is a governance concern that falls squarely within the Social pillar of ESG.

Bias and opacity in talent decisions. Hiring and promotion tools trained on historical data can reproduce existing patterns of disadvantage. Raghavan et al. (2020) find that vendors of algorithmic pre-employment assessments provide limited public detail on how bias is defined, measured, and mitigated, which hampers scrutiny by employers and regulators. Fairness, non-discrimination, and transparency are central themes across ethics guidelines (Jobin et al., 2019; UNESCO, 2021), and neglecting them conflicts directly with the inclusion objectives of the ESG Social pillar.



## **6. The Indian and Kerala Context**

### **6.1 Indian IT and the headcount-linked model**

India's software services industry grew on an export orientation and a large supply of engineering talent (Arora et al., 2001). This heritage shapes its exposure to cognitive automation. Service lines that depend on routine development, testing, and documentation are those in which AI-assisted productivity gains are most likely to change the relationship between headcount and revenue. National policy has begun to articulate principles for responsible AI adoption (NITI Aayog, 2021), but firm-level governance instruments remain at an early stage

### **6.2 Kerala's technology parks**

Kerala's IT sector operates largely through state-promoted parks under unified government infrastructure initiatives, and STPI (2025) places the state eighth nationally in software export volume. Technopark in Thiruvananthapuram, one of India's earliest technology parks, expanded direct employment from 52,746 professionals in 2016–17 to 80,000 in 2024–25 (Deshabhimani, 2025; Technopark, 2024). Over the shorter 2020–21 to 2024–25 window, employment rose from 63,000 to 80,000 (27%) while export revenues rose by 56% (Deshabhimani, 2025). Technopark's exports grew from ₹8,255 crore to ₹14,575 crore between 2016–17 and 2024–25.

Infopark in Kochi recorded ₹11,417 crore in IT exports in 2023–24, a 24.28% year-on-year increase (Onmanorama, 2024), and by April 2024 hosted more than 70,000 professionals across more than 580 registered companies (Infopark, 2024; Onmanorama, 2024). Cyberpark in Kozhikode extends the park network to northern Kerala, and state initiatives such as Technocity and the Indeevaram start-up facility broaden the ecosystem (Kerala State Planning Board, 2026).

### **6.3 Descriptive evidence on export–employment dynamics**

In the absence of firm-level data on AI deployment, this review illustrates the export–employment relationship using park-level secondary data and simple growth rates, computed as:

$$\text{Growth rate (\%)} = [(V_t - V_{t-1}) / V_{t-1}] \times 100 \quad (1)$$

where  $V$  denotes the value of the indicator in period  $t$ . To make the comparison more informative, export revenue per direct employee is also derived as the ratio of reported export revenue to reported employment. All values are nominal and rupee-denominated. Tables 2 and 3 report the results.



**Table 2.** *Employment and IT exports in major Kerala IT parks, 2023–25*

| Indicator                                | 2023–24 | 2024–25 | Growth (%) |
|------------------------------------------|---------|---------|------------|
| Aggregate direct employment              | 147,200 | 155,300 | +5.50      |
| Aggregate IT exports (₹ crore)           | 24,793  | 26,770  | +7.97      |
| Export revenue per employee<br>(₹ lakh)* | 16.84   | 17.24   | +2.34      |

*Note.* Compiled from Kerala State Planning Board (2026), Technopark (2024), Infopark (2024), and STPI (2025). \*Derived by the authors. 1 crore = 10 million; 1 lakh = 100,000.

**Table 3.** *Technopark long-term growth, 2016–25*

| Indicator                                | 2016–17 | 2024–25 | Growth (%) |
|------------------------------------------|---------|---------|------------|
| Direct employment                        | 52,746  | 80,000  | +51.7      |
| Export revenue (₹ crore)                 | 8,255   | 14,575  | +76.6      |
| Export revenue per employee<br>(₹ lakh)* | 15.65   | 18.22   | +16.4      |

*Note.* Compiled from Deshabhimani (2025) and Technopark (2024). \*Derived by the authors.

Two patterns emerge. Over 2023–25, aggregate exports grew by 7.97% against 5.50% for employment, an employment-export growth ratio of about 0.69. Over the longer 2016–17 to 2024–25 window, Technopark’s exports grew by 76.6% against 51.7% for direct employment (a ratio of about 0.68), and export revenue per employee rose by about 16.4%. Absolute employment expanded in both periods, so the data show no evidence of headcount decline. They do show a persistent gap between output growth and employment growth.



This gap should be read with caution. It is consistent with productivity-led task automation, in which output grows through technological deepening rather than proportional headcount expansion (Acemoglu & Restrepo, 2018). It is equally consistent with other explanations: rupee depreciation, which inflates rupee-denominated export values; changes in pricing and contract structure; a shift toward higher-value service lines; and the maturing of offshore delivery models. Over the short 2023-25 window, nominal export revenue per employee rose by only about 2.3%, a figure unlikely to reflect real productivity gains once general price changes are accounted for. The data are therefore best treated as descriptive context that motivates governance attention, rather than as evidence that AI has already displaced workers. Establishing attribution would require firm-level data on AI adoption, real-value series, and service-line disaggregation (Section 10).

#### **6.4 Kerala's contextual position**

Kerala combines a highly educated workforce, a decentralised network of parks, and coordination through park authorities. This combination may make reskilling and governance interventions easier to organise than in larger, more fragmented metropolitan clusters. By elevating worker capabilities from routine task execution toward systems engineering, ethical governance, and complex domain architecture, the state could build an export model that is more resilient to low-level automation. To the authors' knowledge, this remains a hypothesis rather than a tested finding, and it is carried forward as Proposition 3 in Section 8.

#### **7. Synthesis: Themes and Gaps**

Table 4 consolidates the review. Taken together, the literature offers a robust task-based account of exposure, emerging evidence that augmentation can raise productivity, a set of ethical principles for AI, and a corporate-governance vocabulary drawn from stakeholder theory and ESG. What it lacks is an integrated, operational bridge between these strands, particularly for regional IT ecosystems in emerging economies.

**Table 4.** *Thematic synthesis and research gaps*

| <b>Theme</b>  | <b>What the literature establishes</b>                                                                                                                                              | <b>Gap addressed in this paper</b>                                                                              |
|---------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|
| Task exposure | Exposure spans routine and, increasingly, non-routine cognitive tasks (Autor et al., 2003; Felten et al., 2021; Eloundou et al., 2024); exposure is not equivalent to displacement. | Exposure evidence is built largely on US occupational data; regional mapping for Indian IT clusters is limited. |



| Theme                           | What the literature establishes                                                                                                                                                                                         | Gap addressed in this paper                                                                                  |
|---------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------|
| Augmentation vs. substitution   | Outcomes depend on design and managerial choices; gains are largest for less experienced workers (Raisch & Krakowski, 2021; Brynjolfsson et al., 2023; Noy & Zhang, 2023).                                              | Little evidence on how augmentation-first policies affect career progression in export-oriented IT services. |
| ESG scope                       | Scholarship centres on the financial relevance and measurement of ESG (Gillan et al., 2021; Berg et al., 2022).                                                                                                         | Workforce consequences of AI are seldom the explicit focus of ESG frameworks.                                |
| Algorithmic management and bias | Algorithms can direct, evaluate, and constrain workers (Kellogg et al., 2020); hiring tools raise transparency concerns (Raghavan et al., 2020); ethics principles converge (Jobin et al., 2019; Floridi et al., 2018). | Principles are seldom translated into auditable, firm-level indicators.                                      |
| Regional evidence               | Indian IT was built on export orientation and skilled labour (Arora et al., 2001); Kerala's parks show expanding employment and revenue (Deshabhimani, 2025; STPI, 2025).                                               | No integrated view linking park-level trajectories to AI exposure and ESG governance.                        |

## 8. Conceptual Framework

### 8.1 The five-stage Kerala AI-ESG Workforce Model

To operationalise the architectural conception of ESG, the review proposes a five-stage model that structures the lifecycle of AI integration, human capital development, and ongoing governance (Table 5). The model is derived from the literature synthesised above and is offered as a conceptual contribution to be tested, not as an empirically validated framework.



**Table 5.** *The five-stage Kerala AI-ESG Workforce Model*

| Stage       | Operational content                                                                                                                                                 | Literature anchor                                                    |
|-------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------|
| 1. Identify | Task-level mapping of enterprise workflows to distinguish routine, AI-exposed tasks from judgement-intensive functions requiring contextual reasoning.              | Autor et al., 2003;<br>Felten et al., 2021;<br>Eloundou et al., 2024 |
| 2. Augment  | Integrate AI primarily as developer copilots and analytical assistants that extend human capability rather than as instruments of headcount reduction.              | Raisch & Krakowski, 2021; Brynjolfsson et al., 2023                  |
| 3. Reskill  | Deliver structured, funded training in prompt engineering, AI system architecture, algorithmic auditing, and digital ethics for employees in high-exposure roles.   | Acemoglu & Restrepo, 2018; WEF, 2025                                 |
| 4. Govern   | Apply governance scorecards for workplace health, algorithmic equity, and reskilling participation; require documented human validation of consequential decisions. | Kellogg et al., 2020;<br>Raghavan et al., 2020;<br>UNESCO, 2021      |
| 5. Measure  | Evaluate AI implementation through balanced scorecards that prioritise retention, human-machine synergy, and software quality over labour-cost reduction.           | Gillan et al., 2021;<br>Berg et al., 2022                            |



## 8.2 The Governance Engine

The Governance Engine translates the “Govern” and “Measure” stages into concrete, monitorable indicators across five ESG-relevant dimensions (Table 6). The indicators are deliberately simple, so that firms of different sizes can report them and park administrations can audit them.

**Table 6.** *Governance Engine: dimensions and key performance indicators*

| ESG dimension            | Key performance indicator                                                                                         | Literature anchor                    |
|--------------------------|-------------------------------------------------------------------------------------------------------------------|--------------------------------------|
| Productivity and quality | Time saved per workflow, measured against software defect rates and security outcomes.                            | Brynjolfsson et al., 2023            |
| Inclusion and equity     | Share of the active workforce successfully retrained, disaggregated by gender, age, and other demographic groups. | Raghavan et al., 2020; UNESCO, 2021  |
| Internal mobility        | Annual transition rate of personnel from exposed routine tasks to high-value technical or managerial roles        | Acemoglu & Restrepo, 2018            |
| Privacy and ethics       | Number of formal AI privacy incidents logged and periodic algorithmic bias audits completed.                      | Jobin et al., 2019; NITI Aayog, 2021 |
| Human oversight          | Share of automated operational and HR decisions subject to mandatory, documented human validation.                | Floridi et al., 2018; UNESCO, 2021   |



### **8.3 Propositions**

The framework generates three propositions for future empirical testing:

- P1. Where AI is deployed under an augmentation-first policy with funded reskilling, productivity gains are more likely to coexist with employment retention and upward task mobility than where deployment is driven by cost reduction (Acemoglu & Restrepo, 2018; Raisch & Krakowski, 2021).
- P2. Firms that embed algorithmic oversight, transparency, and bias auditing upstream should experience fewer workforce trust and fairness failures than firms whose ESG activity is confined to disclosure (Jobin et al., 2019; Kellogg et al., 2020; Raghavan et al., 2020).
- P3. In regional clusters with state-backed infrastructure and a highly educated workforce, coordinated public-private reskilling can narrow the gap between output growth and employment growth (Arora et al., 2001; Cazzaniga et al., 2024).

## **9. Implications**

### **9.1 For IT enterprises**

1. Prioritise augmentation-first integration. Structure procurement and system design around tools that extend human capability rather than software that substitutes for labour (Raisch & Krakowski, 2021).
2. Build internal mobility pathways. Link efficiency gains formally to reskilling pipelines, so that retrained workers move into AI system maintenance, data governance, and higher-order engineering roles (Acemoglu & Restrepo, 2018).
3. Audit algorithmic systems. Subject recruitment, performance evaluation, and task-allocation systems to documented, periodic bias and safety reviews, and publish summaries in annual ESG disclosures (Raghavan et al., 2020; UNESCO, 2021).

### **9.2 For park administration and policymakers**

1. Report AI-exposure indicators. Include AI-exposure and structural productivity metrics in annual park performance reporting, building on existing STPI (2025) reporting.
2. Co-fund regional upskilling. Co-sponsor certification. Partner with tenant firms to co-sponsor certification in prompt engineering, algorithmic safety, and complex systems design.
3. Link incentives to governance. Consider tying incentives and space allocation to adoption of a governance dashboard, calibrated to firm size and consistent with responsible-AI principles (NITI Aayog, 2021).

### **9.3 For higher education institutions**

1. Update curricula. Embed human-AI collaboration, digital ethics, and algorithmic governance in undergraduate and postgraduate computing and management programmes.



2. Establish park–academic partnerships. Work with park authorities to assemble firm-level longitudinal data on task exposure, skill transitions, and AI deployment.

## **10. Limitations and Future Research**

### **10.1 Limitations**

Three limitations qualify the review. First, its purposive, non-systematic design means that coverage of the literature is not exhaustive, and the inclusion of institutional and administrative sources introduces variation in evidentiary quality. Second, the regional analysis relies on park-level aggregate, nominal, rupee-denominated data; the observed export–employment divergence cannot be attributed exclusively to AI adoption, because currency movements, pricing and contract shifts, service-mix changes, and process improvements also influence export valuations. Third, international exposure indices are macro-level approximations when applied to Kerala’s specific skill mix and organisational structures, and the proposed model and propositions have not yet been empirically validated.

### **10.2 Research agenda**

Future research should collect primary micro-level data from tenant firms across Kerala’s technology parks and pursue the following directions:

- Construct real-value (deflated or foreign-currency) export series disaggregated by service line, and test the export–employment relationship with firm-level data on AI adoption.
- Track retrained software professionals longitudinally across demographic groups to measure long-term career resilience and the effect of AI assistance on entry-level skill formation.
- Survey firms on capital allocation toward AI software relative to project-delivery models and headcount plans.
- Pilot and validate the Governance Engine in active IT enterprises, and test Propositions 1–3 using comparative designs across Indian states and technology clusters.

## **11. Conclusion**

This review has argued that the governance of AI-driven workforce change is a central, and under-theorised, task for ESG. The literature shows that AI exposure is concentrated in cognitive tasks that were once considered safe from automation, that outcomes for workers depend on whether AI is used to augment or to substitute labour, and that algorithmic management and biased talent systems create Social and Governance risks that disclosure-oriented ESG practice is poorly equipped to manage. Descriptive evidence from Kerala’s technology parks shows employment still expanding but lagging export growth. This pattern warrants governance attention, though it does not yet support claims of AI-driven displacement.



The proposed five-stage model and Governance Engine offer a structured way to move from principle to practice, and the accompanying propositions provide testable claims for future work. Kerala's long-term competitiveness in IT services is likely to depend less on the pace of AI adoption than on whether that adoption is institutionalised through augmentation-first, human-in-the-loop workflows that invest in people alongside technology.

## References

- Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542. <https://doi.org/10.1257/aer.20160696>
- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188–2244. <https://doi.org/10.1086/705716>
- Arora, A., Arunachalam, V. S., Asundi, J., & Fernandes, R. (2001). The Indian software services industry. *Research Policy*, 30(8), 1267–1287. [https://doi.org/10.1016/S0048-7333\(00\)00151-0](https://doi.org/10.1016/S0048-7333(00)00151-0)
- Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3), 3–30. <https://doi.org/10.1257/jep.29.3.3>
- Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279–1333. <https://doi.org/10.1162/003355303322552801>
- Berg, F., Kölbels, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6), 1315–1344. <https://doi.org/10.1093/rof/rfac033>
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at work* (NBER Working Paper No. 31161). National Bureau of Economic Research. <https://doi.org/10.3386/w31161>
- Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
- Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E., & Tavares, M. M. (2024). *Gen-AI: Artificial intelligence and the future of work* (IMF Staff Discussion Note SDN/2024/001). International Monetary Fund.
- Deshabhimani. (2025, July 2). Technopark hits 80,000 jobs, sees 56% rise in software exports in 5 years. *Deshabhimani English*.
- Donaldson, T., & Preston, L. E. (1995). The stakeholder theory of the corporation: Concepts, evidence, and implications. *Academy of Management Review*, 20(1), 65–91. <https://doi.org/10.5465/amr.1995.9503271992>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. *Science*, 384(6702), 1306–1308. <https://doi.org/10.1126/science.adj0998>



- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. <https://doi.org/10.1002/smj.3286>
- Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28(4), 689–707. <https://doi.org/10.1007/s11023-018-9482-5>
- Freeman, R. E. (1984). *Strategic management: A stakeholder approach*. Pitman.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of ESG and CSR research in corporate finance. *Journal of Corporate Finance*, 66, Article 101889. <https://doi.org/10.1016/j.jcorpfin.2021.101889>
- Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and jobs: A global analysis of potential effects on job quantity and quality* (ILO Working Paper 96). International Labour Organization.
- Infopark. (2024). *Infopark annual growth and export review 2023–24*. Infopark Kochi, Government of Kerala Society.
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399. <https://doi.org/10.1038/s42256-019-0088-2>
- Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals*, 14(1), 366–410. <https://doi.org/10.5465/annals.2018.0174>
- Kerala State Planning Board. (2026). *Kerala development report 2026: Economic transformation and tech-ecosystem dynamics*. Government of Kerala.
- NITI Aayog. (2021). *Responsible AI #AIforAll: Approach document for India, Part 1—Principles for responsible AI*. Government of India.
- Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654), 187–192. <https://doi.org/10.1126/science.adh2586>
- OECD. (2023). *OECD employment outlook 2023: Artificial intelligence and the labour market*. OECD Publishing.
- Onmanorama. (2024, September 4). Infopark clocks Rs 11,417 cr from IT exports at 24.28% growth. *Onmanorama*.



- Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 469–481). ACM. <https://doi.org/10.1145/3351095.3372828>
- Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Software Technology Parks of India. (2025). *Indian software exports and state-wise performance evaluation 2024–25*. Ministry of Electronics and Information Technology, Government of India.
- Technopark. (2024). *Technopark performance overview and employment report 2023–24*. Electronics Technology Parks–Kerala.
- UNESCO. (2021). *Recommendation on the ethics of artificial intelligence*. United Nations Educational, Scientific and Cultural Organization.
- World Economic Forum. (2025). *The future of jobs report 2025*. World Economic Forum.