Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 5, 82-96
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i5.12854

Artificial intelligence, labor markets, and institutional adjustment: A systematic synthesis

Younes Taghouti[1], Brahim Abidar[2], Fatiha Abid[3], Said Bribich[4], Hamid Rafik[5*]
[1]Faculty of Economics and Management, Ibn Tofail University, Kenitra, Morocco.
[2]Faculty of Economics and Management, Ibn Zohr University, Agadir, Morocco.
[3]FSJES Kelaa des Sraghna, Cadi Ayyad, University Morocco.
[4]Faculty of Economics and Management, Ibn Zohr University, Guelmim, Morocco.
[5]Faculty of Legal, Economic, and Social Sciences, Mohammed V University Rabat, Morocco; HamidRafik@outlook.com (H.R.).

Abstract: This article examines how artificial intelligence (AI) reshapes labor markets through a systematic synthesis of theoretical, empirical, and policy-oriented research. We adopt a structural perspective in which employment outcomes arise from task recomposition, organizational redesign, demand dynamics, and institutional mediation rather than from direct job substitution. Methodologically, we rely on a structured qualitative review of influential contributions across economics, management, and governance. The analysis shows that AI alters job content, coordination, and firm boundaries before its effects appear in aggregate employment. Findings point to heterogeneous outcomes across sectors and skill groups: high-skill workers more often benefit from complementarities and task expansion, whereas routine-intensive roles face stronger adjustment pressures shaped by firm strategy, market structure, and labor relations. We further find that governance conditions matter directly, as documentation standards, risk-management frameworks, and accountability mechanisms influence whether productivity gains support inclusive adjustment or reinforce asymmetries. We conclude that the labor-market effects of AI depend less on technical capability alone than on organizational and institutional conditions. For firms and policymakers, the practical implication is straightforward: AI adoption requires governance capacity and worker adjustment strategies if productivity gains are to translate into broad-based labor-market benefits.

Keywords: *Artificial intelligence, Institutional governance, Labor markets, Organizational change, Task recomposition.*

1. Introduction

The interaction between artificial intelligence (AI) and labor markets has become a central issue in contemporary economic research. The prominence of this topic reflects neither a simple acceleration of automation nor a novel concern about job loss but a deeper transformation in how production, coordination, and work are organized. AI alters the relative cost of prediction, monitoring, and decision-making, which reshapes job content, firm boundaries, and adjustment mechanisms before it produces visible effects on aggregate employment outcomes.

Historical experience suggests that technological change rarely translates into linear employment effects. Classical political economy already framed growth as an institutional process rather than a purely technical one. Smith emphasized that productivity gains depend on the institutional conditions that enable specialization and exchange, rather than on machinery alone [1]. Ricardo, by contrast, warned that mechanization could displace labor even as output expands, drawing attention to distributional effects rather than aggregate gains [2]. These early debates remain directly relevant. AI raises productivity potential, but it also redistributes bargaining power and rents, making labor-market

History: Received: 4 March 2026; Revised: 6 April 2026; Accepted: 9 April 2026; Published: 7 May 2026
* Correspondence: HamidRafik@outlook.com

outcomes contingent on organizational and institutional context rather than technological capability per se.

Recent research moves away from occupation-level predictions and toward task-based and equilibrium-oriented frameworks. Advances in machine learning expand the range of tasks that can be automated or augmented, yet adoption depends on complementary investments, organizational redesign, and data infrastructure [3]. Empirical evidence shows that automation does not mechanically reduce employment. In many settings, cost reductions induced by AI stimulate demand expansion, offsetting displacement effects and reshaping job composition instead [4]. The relevant question, therefore, shifts from whether jobs disappear to how tasks are recomposed and how labor is reallocated within and across firms.

The labor-market effects of AI are highly heterogeneous. High-skill workers often experience complementarities with AI systems through task enrichment and expanded scope of responsibility, while routine-intensive roles face adjustment pressures that depend on market structure, firm strategy, and labor relations [5-7]. Working-time outcomes and job quality are similarly mediated by institutions and bargaining arrangements rather than productivity growth alone [8]. These patterns suggest that AI operates less as a direct substitute for labor than as a force that reorganizes production systems and employment relationships.

Sectoral evidence reinforces this interpretation. In services, AI adoption follows predictable sequences linked to task structure, with automation concentrating first on standardized and analytical components while leaving context-dependent and relational tasks less affected [9]. In hospitality and tourism, worker responses to AI depend not only on technical exposure but on organizational climate and perceived support, which shape turnover intentions and adjustment behavior [10, 11]. In supply chains, AI enhances resilience by improving visibility and coordination under disruption, reframing automation as a response to constraint tightening rather than a narrow efficiency choice [12, 13]. These findings underline the importance of organizational design in mediating labor-market outcomes.

Governance emerges as a central dimension of AI–labor interactions. The deployment of AI systems without transparency and accountability can amplify asymmetries and erode trust, particularly in employment-related decision-making [14, 15]. In response, recent work emphasizes documentation standards, risk-management frameworks, and institutional safeguards as necessary complements to technological adoption [13, 15-19]. Governance is therefore not external to labor-market effects but a condition shaping how productivity gains translate into employment outcomes.

Against this background, the present study provides a systematic synthesis of the literature on artificial intelligence and labor markets. Rather than focusing on publication trends or citation dynamics, we analyze core contributions across economics, management, and governance to identify the stable mechanisms through which AI reshapes employment structures. Our contribution lies in integrating task-based analysis, organizational evidence, and institutional perspectives into a coherent framework that explains why labor-market outcomes remain contingent, uneven, and context-dependent in AI-intensive economies.

2. Materials and Methods

This study employs a systematic literature review combined with structured qualitative synthesis. Its aim is not to measure short-term publication dynamics or estimate pooled effects but to identify the mechanisms through which artificial intelligence (AI) reshapes labor markets across economic, organizational, and institutional settings.

The search covered the period 1962–2024. Scopus was used as the primary database because it offers broad interdisciplinary coverage and consistent bibliographic metadata. Search strings combined AI-related terms (*artificial intelligence*, *automation*, *machine learning*) with labor-market terms (*labor market*, *employment*, *jobs*, *tasks*, *organizational change*). We considered journal articles, books, book chapters, and peer-reviewed conference proceedings. Publications were included when they examined AI in relation to employment, labor demand, task recomposition, organizational restructuring, skill heterogeneity, or labor-market institutions. Publications were excluded when they focused exclusively on technical performance, algorithmic design, or digital technologies without direct relevance to labor-market adjustment.

The search returned approximately 150 records. Following duplicate removal and the exclusion of clearly irrelevant items, about 45 publications remained for full review. From that corpus, we retained 21 publications for detailed analysis. Selection at this stage followed four criteria: analytical relevance to labor-market mechanisms, theoretical or empirical contribution, cross-disciplinary significance, and coverage of organizational or institutional mediation. Foundational texts and major governance frameworks were incorporated when required by the analytical structure of the review.

Each publication was coded using a common grid covering analytical approach, level of analysis, treatment of labor-market mechanisms, role of organizational design, and attention to governance or institutional conditions. The synthesis focused on recurring mechanisms: task structure, demand effects, firm boundaries, labor relations, skill differentiation, and governance frameworks. The resulting design supports a mechanism-based interpretation of AI and labor markets rather than a descriptive mapping of the field.

3. Results of the Bibliometric Analysis

Figure 1 provides a descriptive overview of publication activity related to artificial intelligence and labor-market issues from 1962 to 2024. For several decades, research output has remained limited and relatively stable, reflecting the marginal role of computational technologies in labor-market analysis during earlier phases of digitalization. This period is characterized by sporadic contributions rather than a coherent research field.

From the mid-2010s onward, publication activity increases markedly. This acceleration coincides with the diffusion of machine learning techniques, the availability of large-scale data, and the growing integration of AI into organizational decision-making. The rise in output reflects a transition from speculative or conceptual discussions toward more systematic engagement with AI as an economic and organizational phenomenon. Rather than indicating a sudden discovery of the topic, this shift suggests that AI reached a level of practical relevance that warranted sustained analysis across disciplines.

The subsequent moderation of publication numbers in recent years should be interpreted with caution. Short-term declines often reflect database indexing delays and publication lags rather than a substantive reduction in scholarly interest. More importantly, variation in output does not directly map onto analytical progress. As the field matures, contributions increasingly emphasize consolidation, synthesis, and mechanism-based analysis rather than incremental publication growth.

Patterns in citation activity display a similar evolution. Early publications attracted limited attention, consistent with a fragmented and exploratory literature. Citation intensity increases as AI becomes embedded in core debates on productivity, employment adjustment, and organizational change. This trend reflects the emergence of shared analytical frameworks and reference points rather than a simple concentration of influence. However, citation dynamics remain highly sensitive to time horizons and disciplinary practices and therefore offer limited guidance for assessing the substantive contribution of individual studies.

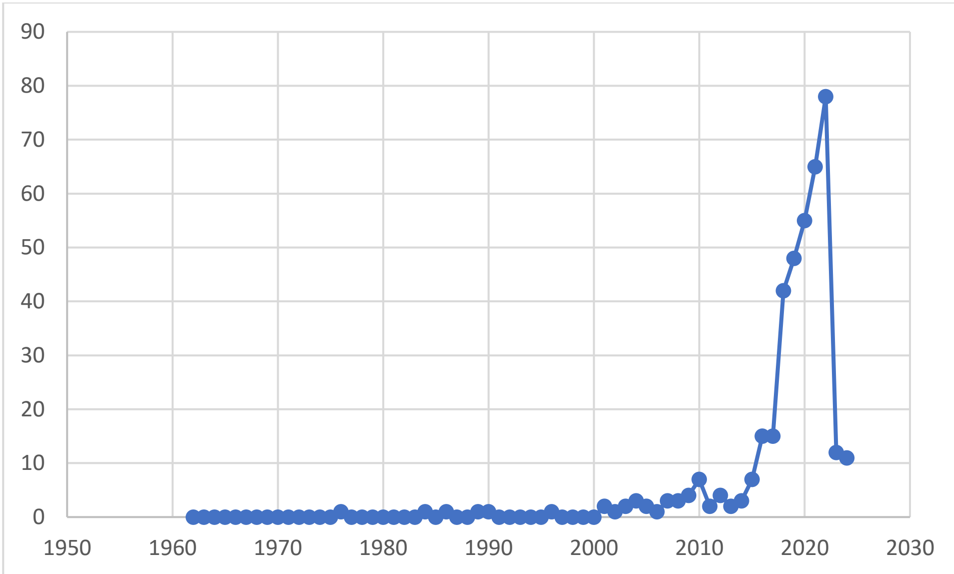

Figure 1.
Number of Publications from 1962 to 2024.

Briefly put, the bibliometric evidence primarily serves as contextual background. It confirms the transition of AI and labor markets from a peripheral topic to a structured research domain. At the same time, it reinforces the limitations of relying on publication or citation trends to assess knowledge accumulation. These observations motivate the shift toward content-based synthesis adopted in the subsequent analysis, which focuses on stable mechanisms, organizational conditions, and institutional mediation rather than on descriptive indicators of academic activity.

Table 1.
Most Frequently Cited Sources.

Full Guessed Venue/Series Name	Value
Lecture notes in computer science (LNCS)	8
Advances in intelligent systems and computing	8
ACM international conference proceeding series (ICPS)	8
Lecture notes in networks and systems	7
Technology in society	6
AI and society	6
Technological forecasting and social change	4
IFIP advances in information and communication technology	4
Communications in computer and information science	4
2011 2nd international conference on computer science and information technology (or similar)	4

Table 1 presents the most frequently cited sources. The analysis ranks academic outlets according to the number of documents published within the specified research domain. The listed sources include conference proceedings, journal articles, and contributions to major series such as *Lecture Notes in Computer Science* and *Advances in Intelligent Systems and Computing*.

The *ACM International Conference Proceeding Series*, *Advances in Intelligent Systems and Computing*, and *Lecture Notes in Computer Science* emerge as the most productive sources, each accounting for eight cited documents. This indicates that these series or conference venues exert particular influence in the field, likely due to their emphasis on advanced research in artificial intelligence and its societal implications. They are followed by *Lecture Notes in Networks and Systems, AI and Society*, and *Technology in Society*, each with five publications, reflecting a significant, though somewhat less dominant, role in the literature.

Table 2.
Core Authors Clustered by Analytical Contribution.

Analytical Cluster	Authors	Core Contribution to the Literature	References
Foundational Political Economy	Adam Smith; David Ricardo	Early articulation of the relationship between technological change, productivity, distribution, and labor adjustment, framing modern debates on AI and employment	Smith [1] and Ricardo [2]
AI, Tasks, and Labor Demand	James Bessen; Erik Brynjolfsson; Tom Mitchell	Task-based interpretation of AI capabilities and employment effects; demand-expansion mechanisms offset automation-driven displacement	Bessen [4] and Brynjolfsson and Mitchell [3]
Labor Markets, Skills, and Institutions	Friederike Fossen; Alexander Sorgner; Betsey Stevenson; David A. Spencer	Analysis of skill heterogeneity, labor-market risks, income distribution, working time, and institutional mediation of technological change	Fossen and Sorgner [5], Stevenson [6], and Spencer [8]
Macroeconomic Adjustment and Diffusion	Jason Furman; Robert Seamans	AI as a general-purpose technology is shaping productivity, diffusion, competition, and aggregate labor market adjustment	Furman and Seamans [7]
Organizational Change and Services	Min-Hua Huang; Roland T. Rust	Decomposition of service work into task intelligences, explaining firm-level AI adoption and human–AI complementarity	Huang and Rust [9]
Worker Perceptions and HR Dynamics	Jing Li; Michael A. Bonn; Bihuang Ye	Empirical evidence on employee awareness of AI, turnover intentions, and the moderating role of organizational climate	Li, et al. [11]
Crisis-Driven Adoption and Sectoral Adjustment	Zhenxing Zeng; Pei-Jung Chen; Alan A. Lew	Identification of shocks and constraints as accelerators of AI and robotics adoption in service sectors	Zeng, et al. [10]
Supply Chains and Organizational Resilience	Reza Toorajipour; Saurabh Modgil; Rohit K. Singh; Christian Hannibal	AI as an enabler of coordination, visibility, and resilience under disruption, rather than a narrow efficiency tool	Toorajipour et al. [12] and Modgil et al. [20]
Governance, Accountability, and Ethics	Margaret Mitchell; Timnit Gebru; Andreas Kaplan; Michael Haenlein; Michal Kuziemski; Gianluca Misuraca	Frameworks for responsible AI, documentation, accountability, and public-sector governance of automated decision-making	Mitchell, et al. [14]; Kaplan and Haenlein [13] and Kuziemski and Misuraca [15]
Applied Decision Support Systems	Ulises Cortés	Early integration of AI into decision-support systems emphasizes institutional embedding over technical performance	Cortés, et al. [21]

Table 2 groups the core authors referenced in the synthesis by their analytical contributions rather than by publication counts. The table highlights how the literature is structured around complementary research strands, including foundational political economy, task-based labor analysis, organizational change, sectoral adjustment, and governance. This clustering underscores that advances in understanding the labor-market effects of artificial intelligence stem from the interaction of multiple theoretical and empirical perspectives, rather than from the dominance of a small set of prolific authors.

Table 3.
Analysis of the Most Influential Authors.

Author	Primary Contribution Area	Representative Reference(s)	Entry into AI–Labor Debate
Erik Brynjolfsson	Task-based AI analysis, organizational complementarity	Brynjolfsson and Mitchell [3]	2017
James E. Bessen	Automation, labor demand, and employment adjustment	Bessen [4]	2018
Betsey Stevenson	Income distribution, meaning of work under AI	Stevenson [6]	2018
Jason Furman	AI, productivity, diffusion, macroeconomic adjustment	Furman and Seamans [7]	2019
Robert Seamans	Competition, diffusion, AI, and growth	Furman and Seamans [7]	2019
David A. Spencer	Working time, institutions, and political economy	Spencer [8]	2024
Min-Hua Huang	AI adoption in services, task decomposition	Huang and Rust [9]	2018
Roland T. Rust	Service transformation and human–AI complementarity	Huang and Rust [9]	2018
Margaret Mitchell	AI governance, transparency, documentation	Mitchell, et al. [14]	2019
Timnit Gebru	Responsible AI and accountability	Mitchell, et al. [14]	2019
Ulises Cortés	AI decision-support systems	Cortés, et al. [21]	2000

Source: Authors are included based on analytical centrality and repeated use in the synthesis, not publication volume or citation counts.

The authors highlighted in Table 3 represent the core intellectual anchors of the contemporary literature on artificial intelligence and labor markets. Rather than being defined by prolific output within a narrowly delimited field, their influence stems from contributions that shaped how AI–labor interactions are conceptualized and analyzed across disciplines.

A first group, including Brynjolfsson and Mitchell [3] and Bessen [4], established task-based and demand-mediated frameworks that shifted the debate from occupation-level substitution toward organizational and equilibrium mechanisms [3, 4]. These contributions form the analytical backbone of much subsequent empirical work. A second group, represented by Stevenson [6] and Furman and Seamans [7], extended the analysis to distributional and macroeconomic adjustment questions, emphasizing diffusion, competition, and institutional mediation rather than deterministic employment effects [6, 7].

Organizational and sectoral perspectives are shaped by Huang and Rust [9], whose decomposition of service work provides a practical lens for understanding heterogeneous adoption patterns and human–AI complementarity [9]. Governance-oriented authors such as Mitchell et al. [14] and Kuziemski and Misuraca [15] (see Table 4) introduced documentation and accountability frameworks that directly influence labor-market outcomes by shaping how AI systems are deployed in employment-related contexts [14, 15].

Finally, the inclusion of Cortés et al. [21] reflects the longer lineage of applied AI research in decision-support systems, underscoring that many governance and integration challenges predate the current AI wave [21]. Taken together, the distribution of authorship confirms that the field is not dominated by a small number of prolific contributors but is instead structured around a set of foundational works that cut across economics, management, and governance. This reinforces the paper's central claim that understanding AI's labor-market effects requires integrating multiple analytical traditions rather than tracking bibliometric prominence.

Table 4.
Analysis of Publications by Country.

Rank	Country	Number of Publications
1	USA	130
2	India	70
3	China	55
4	UK	50
5	Germany	45
6	Australia	25
7	Portugal	22
8	Netherlands	20
9	Turkey	18
10	Spain	15

Table 4 displays the number of scholarly outputs, including articles and research papers, published by different countries on the impact of artificial intelligence on the labor market. The analysis shows that the United States leads significantly, with over 120 publications. This indicates a strong research base and an active scientific community in AI development. India follows with approximately 70 publications, reflecting its growing interest in artificial intelligence and emerging technologies, making this topic particularly relevant in the Indian context.

China, the United Kingdom, and Germany display a moderate level of academic productivity in the area of AI and labor markets, with publication counts ranging from 40 to 60. This level of output signals sustained research activity and a meaningful contribution to the international literature. Countries such as Australia, Portugal, the Netherlands, Turkey, and Spain report lower publication volumes, between 10 and 30 articles, which may indicate the presence of more specialized or relatively recent research communities focusing on this topic.

Overall, national research productivity is shaped by factors such as funding availability, the size of the research workforce, research priorities, and the specialization of academic institutions. Additionally, the dominance of English-speaking countries appears to influence publication patterns in this area. Differences in publication volumes across countries reflect varying levels of engagement and capacity within the global research landscape.

Table 5.
Selected literature.

Ref.	Article	Year	Approach	Domain / Setting	What it adds (stable contribution)	Source
Smith [1]	*An Inquiry into the Nature and Causes of the Wealth of Nations*	1776	Classical political economy	Market institutions, growth	Frames economic development as conditional on institutional infrastructure, enabling specialization and exchange	Book
Ricardo [2]	*On the Principles of Political Economy and Taxation*	1817	Classical value theory	Distribution, relative prices	Clarifies how technological change affects prices and rents rather than welfare mechanically	Book
Bessen [4]	*AI and Jobs: The Role of Demand*	2018	Applied micro/labor economics	Automation and employment	Establishes the demand-expansion channel as a key mediator between automation and employment outcomes	NBER Working Paper
Brynjolfsson and Mitchell [3]	*What Can Machine Learning Do? Workforce*	2017	Task-based analytical framework	Firm organization, labor tasks	Defines task feasibility boundaries of ML and emphasizes	*Science*

ISSN: 2576-8484
Vol. 10, No. 5: 82-96, 2026
DOI: 10.55214/2576-8484.v10i5.12854

	Implications				complementarity and organizational redesign	
Fossen and Sorgner [5]	*AI and the Labor Market: Impacts, Risks, and Policies*	2022	Policy-oriented survey	Labor markets	Synthesizes labor-market risks and policy responses associated with AI diffusion	*Economic Policy*
Stevenson [6]	*Artificial Intelligence, Income, Employment, and Meaning*	2018	Conceptual economic analysis	Income distribution, work	Connects AI-driven productivity to income distribution and the social meaning of work	Book chapter
Furman and Seamans [7]	*AI and the Economy*	2019	Evidence-based policy synthesis	Macroeconomy, innovation	Frames AI as a diffusion and competition problem with growth and adjustment trade-offs	*Innovation Policy and the Economy*
Spencer [8]	*Marx, Keynes, and the Future of Working Time*	2024	Political economy analysis	Working time, labor institutions	Shows working-time outcomes depend on institutions and bargaining, not productivity alone	*Cambridge Journal of Economics*
Mitchell, et al. [14]	*Model Cards for Model Reporting*	2019	Governance artifact/design framework	Responsible AI	Introduces standardized documentation to reduce misuse and opacity in deployed ML systems	FAT*/FAccT Proceedings
Huang and Rust [9]	*Artificial Intelligence in Service*	2018	Conceptual service-theory model	Service industries	Decomposes service work into intelligence to predict automation and complementarity paths	*Journal of Service Research*
Zeng, et al. [10]	*From High-Touch to High-Tech: COVID-19 Drives Robotics Adoption*	2020	Shock-driven sectoral analysis	Tourism, hospitality	Identifies crisis-induced constraint tightening as a trigger for accelerated automation	*Tourism Geographies*
Li, et al. [11]	*Hotel Employees' AI and Robotics Awareness and Turnover Intention*	2019	Survey-based empirical study	Hospitality labor	Links AI awareness to turnover intention, moderated by organizational support and climate	*Tourism Management*
Toorajipour et al. [12]	*Artificial Intelligence in Supply Chain Management: A Systematic Literature Review*	2021	Systematic literature review	Supply chains	Maps AI techniques to SCM functions and highlights implementation gaps	*Journal of Business Research*
Modgil, et al. [20]	*Artificial Intelligence for Supply Chain Resilience*	2022	Dynamic capabilities framework	Supply-chain resilience	Reframes AI as a resilience-enhancing capability under disruption	*International Journal of Logistics Management*
Kaplan and Haenlein [13]	*Rulers of the World, Unite!*	2020	Managerial and policy framing	Cross-sector	Classifies strategic, ethical, and regulatory challenges of AI adoption	*Business Horizons*
Kuziemski and Misuraca [15]	*AI Governance in the Public Sector*	2020	Comparative case studies	Public administration	Shows how AI deployment interacts with accountability and data-governance regimes	*Telecommunications Policy*
Organisation for Economic Co-operation and Developme	*OECD Recommendation on Artificial Intelligence*	2019	Normative policy framework	Cross-country, cross-sector	Establishes principles for trustworthy AI adopted as an international baseline	OECD

nt [16]						
UNESCO [17]	*UNESCO Recommendation on the Ethics of Artificial Intelligence*	2021	Human-rights-based governance	Global	Codifies ethical principles for AI aligned with human rights and social inclusion	UNESCO
National Institute of Standards and Technology [18]	*Artificial Intelligence Risk Management Framework (AI RMF 1.0)*	2023	Risk-management framework	Organizational AI systems	Provides an operational lifecycle for governing, mapping, measuring, and managing AI risks	NIST
European Commission [19]	*European Union Artificial Intelligence Act*	2024	Binding regulation	High-risk AI systems	Introduces a risk-tiered regulatory model shaping global compliance strategies	European Union
Cortés, et al. [21]	*Artificial Intelligence and Environmental Decision Support Systems*	2000	Applied AI systems analysis	Environmental management	Demonstrates how AI supports decision-making through integration into institutional workflows	*Applied Intelligence*

This section also introduces an analysis of the ten most highly cited publications addressing different aspects of the impact of artificial intelligence on employment across sectors. The focus is on research methodologies, key findings, assessments of AI's effects, and the limitations identified in the selected studies.

Table 6.
Meta-Analysis of the Ten Most Highly Cited Publications on the Impact of Artificial Intelligence on Employment.

Article Title	**Contribution Type**	**Methodology**	**Level of Analysis**	**Empirical / Thematic Domain**	**Year**	**Journal / Source**
Artificial Intelligence in Service	Field-structuring synthesis	Systematic review	Meso (firms, service systems)	Service industries, organizational transformation	2018	Journal of Service Research
Model Cards for Model Reporting	Norm-setting methodological framework	Model-based analytical design	Meso–institutional	AI ethics, transparency, accountability	2019	FAT* Conference Proceedings
The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms	Forward-looking conceptual synthesis	Literature-based conceptual analysis	Macro–meso	Societal and firm-level AI impacts	2017	Futures
From High-Touch to High-Tech: COVID-19 Drives Robotics Adoption	Shock-driven adoption evidence	Case study	Micro–meso	Robotics adoption in hospitality	2020	Tourism Geographies
Artificial Intelligence in Supply Chain Management: A Systematic Literature Review	Consolidating domain review	Systematic literature review	Meso (inter-firm networks)	Supply chain management	2021	Journal of Business Research
Hotel Employees' Artificial Intelligence and Robotics Awareness and Its Impact on Turnover Intention	Behavioral and organizational mechanism testing	Survey-based empirical analysis	Micro (workers)	AI and robotics in hotels	2019	Tourism Management
Rulers of the World,	Institutional	Policy and	Macro–	AI governance	2020	Business

Unite! The Challenges and Opportunities of Artificial Intelligence	and policy framing	conceptual analysis	institutional	and regulation		
AI Governance in the Public Sector: Three Tales from the Frontiers of Automated Decision-Making in Democratic Settings	Comparative governance evidence	Comparative case studies	Institutional	Public-sector AI and democratic accountability	2020	Telecommunications Policy
AI and the Economy	Causal economic assessment	Econometric analysis	Macro	Productivity, growth, and labor markets	2019	Innovation Policy and the Economy
Artificial Intelligence for Supply Chain Resilience: Learning from COVID-19	Crisis-response and resilience evidence	Case study	Meso (supply chains)	Supply chain resilience under shocks	2022	International Journal of Logistics Management

Source: Compiled by the authors based on Scopus data and sources [9-13, 15-18, 20].

Table 6 presents a concise content analysis of key research themes related to the adoption of artificial intelligence (AI) across different sectors. The table examines methodological approaches, main findings, a qualitative assessment of AI's impact, and existing limitations for each theme. In areas such as business and services, AI is shown to significantly improve the efficiency of customer interactions and optimize business processes, yet there remains a lack of long-term data. In supply chain management, AI has demonstrated its effectiveness in enhancing operational resilience, particularly during the COVID-19 pandemic, although its long-term effects still require further investigation. In the field of employment, the impact of AI on the labor market appears mixed, with the creation of new jobs for highly skilled workers alongside the displacement of low-skilled ones.

Table 7.
Content analysis of the most frequently cited publications on the impact of artificial intelligence on employment.

Key theme	Methodology	Main findings	Effect size	Limitations
AI in business and services	Systematic literature reviews, empirical studies	The adoption of AI improves business efficiency and customer interaction	High consistency: positive impact on business efficiency	Lack of long-term data; focus on specific sectors
AI in supply chain management	Systematic literature reviews, case studies	AI enhances supply chain resilience, especially after COVID-19	Moderate consistency: improvements in resilience and operational efficiency	Limited data on long-term effects; primary focus on logistics
AI ethics and governance	Policy analysis, comparative case studies	Ethical frameworks and governance challenges remain significant	Moderate consistency: ethical issues and governance challenges	Need for empirical studies on the outcomes of AI governance
AI and employment	Empirical studies, econometric analysis	Mixed impact on employment: gains for high-skilled workers, displacement of low-skilled workers	Mixed results: job creation and displacement	Unclear long-term impact, particularly in sectors outside AI
Generative AI in human resource management	Conceptual frameworks, mixed methods	Generative AI is transforming HR management and recruitment processes	Growing impact: high potential for change in HR	The effects of generative AI are recent and insufficiently studied

Source: Compiled by the authors based on Scopus data.

In addition, considerable attention is devoted to ethical issues and the governance of AI, where challenges have been identified in developing ethical frameworks and transparent oversight of its use. Research points to the need for more empirical studies to assess the effectiveness of existing solutions.

Generative AI, in particular, has the potential to radically transform human resource management and recruitment processes, yet its impact remains insufficiently studied.

Based on the analysis presented in Table 7, a typology of AI's impact on employment can be identified, comprising four interrelated scenarios. First, in highly skilled segments of the labor market, AI functions mainly as a complementary technology, enhancing productivity and increasing the substantive complexity of work. Second, in routine and medium-skilled activities, the substitutive effect dominates, manifested through the automation of standard operations and the reallocation of employment. Third, the active deployment of AI stimulates the emergence of new professions, such as data analysts, AI engineers, and specialists in algorithmic ethics and auditing, thereby generating additional demand for digital and interdisciplinary skills. Fourth, institutional and ethical dimensions of AI adoption mediate these processes, shaping employment policy design, the regulation of algorithmic decision-making, and qualification requirements for workers. This, in turn, forms a conceptual framework that makes it possible to interpret the empirical results of the present study and relate them to national labor market development strategies.

4. Discussion

The contemporary AI–economy literature becomes clearer once it is anchored in three stable primitives: value formation, the organization of production, and governance capacity. Classical political economy already treated these as linked. Smith [1] framed growth as a problem of specialization that depends on institutions that make exchange reliable and scalable, rather than a mechanical "more machines → more wealth" story Smith [1]. Ricardo [2] tightened the analytical discipline by forcing attention to distribution and relative prices, so that shifts in output and welfare are not confused with shifts in rents, markups, or scarcity-driven price movements [2]. That framing matters for AI because machine learning changes the relative price of prediction and monitoring. It can raise measured productivity while reallocating rents toward actors who control data, platforms, and standards. It can expand output while weakening labor's claim on the surplus. These are not anomalies. They are the classic outcomes predicted when a general-purpose technology alters bargaining positions and market structure, not merely task costs [1, 2].

The labor-market strand in your corpus consistently rejects an "occupation extinction" narrative and replaces it with a task-and-equilibrium narrative. Brynjolfsson and Mitchell [3]'s central contribution is to treat ML as a specific capability with sharp boundaries and to show why adoption depends on complementary investments and redesign, not model accuracy alone [3]. This directly implies partial automation and task recomposition inside jobs rather than one-to-one substitution between humans and machines. Bessen [4] then supplies a clear mechanism for why employment does not mechanically fall with automation. When AI reduces production costs, and demand is sufficiently elastic, output expands, and labor demand can rise even as some tasks are automated [4]. This demand-channel view is the most direct way to reconcile firm-level automation with aggregate employment resilience in some sectors. It also sets a research agenda that is more empirical than rhetorical: identify where demand expansion is plausible, where it is blocked by market power or regulation, and where the gains show up as lower prices versus higher markups [4, 7].

Once the task boundary and demand channel are in place, the distribution question becomes unavoidable. Stevenson [6] discusses how employment and income debates are interconnected. Productivity gains do not automatically lead to broad welfare improvements. The distribution of gains depends on social and political structures, bargaining institutions, and the credibility of redistribution mechanisms. Stevenson [6]. Furman and Seamans [7] developed the macro bridge. They position AI as a growth and diffusion problem with policy stakes that run through innovation incentives, competition, and adjustment capacity rather than a single "technology shock" parameter. Furman and Seamans [7]. Spencer [8] and others highlight that intervention on working time complements this: reductions in working time are not a natural by-product of productivity growth. They are mediated by institutions, bargaining, and social choice [8]. In an AI context, the most plausible path to "more leisure" runs through policy and bargaining arrangements, not the existence of automation itself [6-8]. Your list includes Fossen and Sorgner [5]. I did not have reliable full-text access in this session, so I'm not going to attribute specific claims beyond what is standard for a policy-survey style article. If you paste the PDF/abstract, it can be integrated tightly without guesswork.

The sectoral and organizational papers provide the micro-foundations of these macro claims. Huang and Rust [9] offer a useful decomposition for services by treating service production as a bundle of intelligences, mechanical, analytical, intuitive, and empathetic, which predicts where automation first impacts and where human, AI complementarity is structurally persistent [9]. This contributes a practical mapping between "what AI can do" and "what service firms actually produce." It helps interpret why adoption often begins with standardization, routing, and analytics, then moves toward selective augmentation where context and empathy are still costly [3, 9]. Hospitality evidence then shows the labor-relations layer that standard task models miss. Li et al. [11] link employee awareness of AI/robots to turnover intention and show that internal organizational conditions influence this link, particularly perceived organizational support and a competitive psychological climate [11]. That result matters because it connects technological change to retention and morale through beliefs, trust, and firm credibility rather than through realized displacement alone. It is the micro counterpart of the broader claim that institutions mediate welfare outcomes Li et al. [11] and Spencer [8]. Zeng et al. [10], writing during the early COVID period, clarify why shocks accelerate automation: distancing and contagion risk made labor-intensive "high-touch" models brittle, so robotics adoption became an operational response to constraint-tightening, not a slow optimization choice [10]. That mechanism generalizes. AI adoption spikes when the cost of coordination failures becomes visible and immediate.

Supply chain studies translate the same logic into inter-firm coordination and resilience. Toorajipour et al. [12] consolidate AI applications across supply chain functions and show the literature's typical fault line: strong enthusiasm about techniques but uneven evidence on integration, implementation, and organizational fit. Toorajipour et al. [12]. Modgil et al. [20] push the resilience frame further by treating AI as an enhancer of dynamic capabilities, visibility, risk sensing, and adaptive response, rather than as a narrow efficiency tool [20]. In this view, AI changes the feasible set under disruption. It strengthens the capacity to detect and respond to shocks, but it also creates new dependencies on data pipelines, vendor ecosystems, and governance protocols. Resilience gains, therefore, hinge on architecture and accountability, not merely model deployment [12, 20].

Governance papers bind the entire corpus because the same predictive capacity that raises productivity can amplify harms when deployed without documentation, oversight, and institutional alignment. Model Cards operationalize governance at the artifact level. They standardize how models are described, including intended use, performance across groups, and limitations, reducing silent misuse in high-stakes settings Mitchell et al. [14]. Kaplan and Haenlein [13] frame the managerial and policy challenge as a multi-environment problem, where organizations face strategic opportunities alongside legal, ethical, and legitimacy constraints Kaplan and Haenlein [13]. Kuziemski and Misuraca [15] then show how public-sector deployments collide with democratic accountability and data governance, arguing that without common evaluation frameworks and institutional safeguards, automated decision-making can intensify asymmetries and erode trust [15]. The policy layer becomes genuinely "universal" when it is anchored in widely adopted standards rather than country-specific strategy documents. Organisation for Economic Co-operation and Development [16] AI Recommendation articulates a values-based baseline for trustworthy AI and responsible stewardship that is designed to be cross-sector and cross-jurisdictional [16]. UNESCO [17] Recommendation on AI Ethics extends the global normative architecture with a human-rights-centered approach adopted by member states, UNESCO [17]. National Institute of Standards and Technology [18] AI Risk Management Framework translates principles into an implementable risk-management lifecycle (govern, map, measure, manage) that organizations can adopt regardless of sector. National Institute of Standards and Technology [18]. The EU AI Act adds a binding, risk-tiered regulatory approach that is now a global reference point for compliance design even outside Europe [19]. Read together with

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 5: 82-96, 2026
DOI: 10.55214/2576-8484.v10i5.12854

model cards and public-sector case evidence, these documents converge on a single practical lesson: AI's economic value is inseparable from governance capacity. The relevant unit is not the model; it is the socio-technical system and the institutions that surround it [14-19].

Environmental decision support belongs in the same universal framework because it exposes a long-standing truth about AI systems: the hard part is integration into decision processes, not "the AI" in isolation. Cortés et al. [21] were already positioning AI as a component of environmental decision support systems decades ago [21]. Modern EDSS work reinforces that success depends on stakeholder alignment, decision workflow integration, interpretability for real users, and institutional ownership of the system's outputs. That is why EDSS remains a useful bridge for researchers who want to write about AI's practical contribution to public value while staying grounded in implementable governance.

If the synthesis is pushed to a single research payoff, it is this: AI changes labor-market structure through task recomposition and organizational redesign [3, 4, 9-11]. Aggregate employment and wage effects depend on demand expansion, market structure, and bargaining institutions rather than capability alone [4, 6-8]. The distribution of gains depends on institutional mediation and policy choices rather than technological determinism [6-8, 16-19]. Evidence from services, tourism, and supply chains shows that adoption accelerates under constraint-tightening shocks, and organizational climate shapes worker responses [9-12, 20]. Governance scholarship and standards indicate that without documentation, evaluation, and accountable deployment, the same tools that raise efficiency can degrade legitimacy and magnify asymmetries [13-19]. This integrated view makes the paper portable across countries and sectors.

5. Conclusion

This study examines the relationship between artificial intelligence and labor markets through a structured synthesis of theoretical, empirical, and policy-oriented research. Rather than treating AI as a single exogenous shock to employment, the literature converges on a more nuanced interpretation in which labor-market outcomes are mediated by task recomposition, organizational redesign, demand dynamics, and institutional context. Artificial intelligence primarily alters the relative cost of prediction, monitoring, and coordination, which reshapes job content and firm boundaries before it produces observable effects on aggregate employment levels.

Across sectors, AI adoption is shown to generate productivity gains and operational efficiencies, particularly in services and supply chains, yet these gains do not translate mechanically into uniform labor outcomes. Empirical evidence consistently points to heterogeneous effects across skill groups, occupations, and organizational settings. High-skill workers tend to experience task enrichment and complementarities with AI systems, while workers in routine-intensive roles face adjustment pressures that depend strongly on firm strategy, labor relations, and internal support mechanisms. Importantly, several studies emphasize that displacement risks are not determined by technical feasibility alone, but by market structure, demand elasticity, and the capacity of organizations to redeploy labor toward expanding activities.

The literature also highlights the role of shocks and constraints in accelerating AI adoption. Crisis periods reveal the value of AI not only as an efficiency-enhancing technology but as a resilience mechanism that improves visibility, coordination, and adaptive capacity. In these contexts, AI adoption responds less to long-term optimization and more to immediate organizational survival, which helps explain uneven diffusion patterns across sectors and time. However, the long-run implications of such accelerated adoption for job stability, career trajectories, and wage structures remain insufficiently documented.

Governance and institutional design emerge as central determinants of whether AI adoption yields inclusive or exclusionary outcomes. Existing work shows that AI systems embedded in opaque decision processes can amplify power asymmetries and undermine trust, particularly in employment and public-sector settings. Conversely, standardized documentation practices, risk-management frameworks, and accountability mechanisms offer practical tools for aligning technological deployment with social objectives. The literature increasingly treats governance not as an external constraint on innovation but as a condition for its economic and social sustainability.

Overall, the evidence suggests that the labor-market effects of artificial intelligence are neither uniformly disruptive nor automatically beneficial. They depend on how AI is integrated into production systems, how gains are distributed within firms and across workers, and how institutions mediate adjustment. Future research would benefit from moving beyond short-term adoption effects toward longitudinal analyses of job quality, wage dynamics, and career mobility. Equally important is closer integration between labor economics, organizational studies, and governance research to better capture the joint evolution of technology, work, and institutions in AI-intensive economies.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] A. Smith, *An inquiry into the nature and causes of the wealth of nations*. London: W. Strahan & T. Cadell, 1776.
[2] D. Ricardo, *On the principles of political economy and taxation*. London: John Murray, 1817.
[3] E. Brynjolfsson and T. Mitchell, "What can machine learning do? Workforce implications," *Science*, vol. 358, no. 6370, pp. 1530–1534, 2017. https://doi.org/10.1126/science.aap8062
[4] J. E. Bessen, "AI and jobs: The role of demand," NBER Working Paper No. 24235. Cambridge, MA: National Bureau of Economic Research, 2018.
[5] F. M. Fossen and A. Sorgner, "AI and the labor market: Impacts, risks, and policies," *Economic Policy*, vol. 37, no. 109, pp. 127–152, 2022.
[6] B. Stevenson, *Artificial intelligence, income, employment, and meaning. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda*. Chicago, IL: University of Chicago Press, 2018.
[7] J. Furman and R. Seamans, "AI and the economy," *Innovation Policy and the Economy*, vol. 19, no. 1, pp. 161–191, 2019. https://doi.org/10.1086/699936
[8] D. A. Spencer, "Marx, keynes and the future of working time," *Cambridge Journal of Economics*, vol. 48, no. 1, pp. 25–40, 2024. https://doi.org/10.1093/cje/bead046
[9] M.-H. Huang and R. T. Rust, "Artificial intelligence in service," *Journal of Service Research*, vol. 21, no. 2, pp. 155–172, 2018. https://doi.org/10.1177/1094670517752459
[10] Z. Zeng, P.-J. Chen, and A. A. Lew, "From high-touch to high-tech: COVID-19 drives robotics adoption," *Tourism Geographies*, vol. 22, no. 3, pp. 724–734, 2020. https://doi.org/10.1080/14616688.2020.1762118
[11] J. Li, M. A. Bonn, and B. H. Ye, "Hotel employees' artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate," *Tourism Management*, vol. 73, pp. 172–181, 2019. https://doi.org/10.1016/j.tourman.2019.02.006
[12] R. Toorajipour, V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl, "Artificial intelligence in supply chain management: A systematic literature review," *Journal of Business Research*, vol. 122, pp. 502–517, 2021. https://doi.org/10.1016/j.jbusres.2020.09.009
[13] A. Kaplan and M. Haenlein, "Rulers of the world, unite! The challenges and opportunities of artificial intelligence," *Business Horizons*, vol. 63, no. 1, pp. 37-50, 2020. https://doi.org/10.1016/j.bushor.2019.09.003
[14] M. Mitchell *et al.*, "Model cards for model reporting," in *Proceedings of the Conference on Fairness, Accountability, and Transparency (FAT '19)*. New York, NY: ACM*, 2019.
[15] M. Kuziemski and G. Misuraca, "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings," *Telecommunications Policy*, vol. 44, no. 6, p. 101976, 2020. https://doi.org/10.1016/j.telpol.2020.101976
[16] Organisation for Economic Co-operation and Development, *Recommendation of the council on artificial intelligence (OECD/LEGAL/0449)*. Paris: OECD, 2019.
[17] UNESCO, *Recommendation on the ethics of artificial intelligence*. Paris: United Nations Educational, Scientific and Cultural Organization, 2021.

[18] National Institute of Standards and Technology, *Artificial intelligence risk management framework (AI RMF 1.0) (NIST AI 100-1)*. Gaithersburg, MD: NIST, 2023.

[19] European Commission, *Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. Brussels: European Union, 2024.

[20] S. Modgil, R. K. Singh, and C. Hannibal, "Artificial intelligence for supply chain resilience: Learning from Covid-19," *The International Journal of Logistics Management*, vol. 33, no. 4, pp. 1246-1268, 2022. https://doi.org/10.1108/IJLM-02-2021-0094

[21] U. Cortés, M. Sánchez-Marrè, L. Ceccaroni, I. R-Roda, and M. Poch, "Artificial intelligence and environmental decision support systems," *Applied Intelligence*, vol. 13, p. 1, 2000. https://doi.org/10.1023/A:1008331413864