Journal of Ethics in Emerging Technologies & Society
ISSN: e-ISSN: 3117-6003 / p-ISSN: 3117-5996
https://galaxiauniverse.com/index.php/JEETS/issue/archive

Societal Impact Assessment of AI-Driven Automation Systems

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ABSTRACT

AI-driven automation systems are transforming labour markets, organisational structures, and social arrangements at an unprecedented pace, with societal impacts that extend far beyond the immediate efficiency gains to individual deploying organisations. Comprehensive societal impact assessment (SIA) for AI automation -- evaluating impacts on employment, wage distribution, occupational identity, community resilience, democratic participation, and generational opportunity -- is urgently needed but methodologically underdeveloped: most existing impact assessments focus on productivity and efficiency metrics, treating labour market disruption as an externality rather than a primary impact dimension. This paper proposes the AI Automation Societal Impact Assessment Framework (AASIAC), a systematic methodology for comprehensive SIA of AI automation across six impact domains -- employment and labour market, wage distribution, occupational identity and dignity, community and regional economic resilience, democratic and political participation, and intergenerational opportunity -- applied to four automation deployment scenarios: manufacturing AI, service sector AI, professional knowledge work AI, and public sector AI. AASIAC introduces the Societal Impact Severity Score (SISS) and evaluates each scenario against six impact domains using structured expert elicitation (20 economists, sociologists, and political scientists), quantitative economic modelling, and community impact case studies. Key results: professional knowledge work AI (LLM-driven automation) achieves the highest SISS (0.848) due to breadth of occupational disruption and concentration in urban knowledge economy centres; wage distribution impact is the most severe single domain across all scenarios; community resilience is the most neglected impact dimension in current policy analysis. The framework provides SIA methodology guidance for policymakers, technology deployers, and affected communities.

Keywords: societal impact assessment; AI automation; labour markets; wage distribution; occupational displacement; community resilience; intergenerational equity; technology governance

Citation: Garcia et al. [2024]. Societal Impact Assessment of AI-Driven Automation Systems. DOI: https://doi.org/10.5281/zenodo.19188012

Article Information: *Received:* 02 December 2023 *Accepted:* 05 February 2024 *Published:* 30 March 2024

Research Article: *Research Article*

1. Introduction

1.1 The Automation Impact Assessment Gap

AI-driven automation is proceeding at a pace that outstrips the policy and social infrastructure designed to manage technological disruption. McKinsey Global Institute (2023) estimates 30% of work hours globally could be automated by 2030; Goldman Sachs (2023) estimates 300 million jobs could be affected by generative AI globally. Yet the policy response to these projections is limited by incomplete impact assessment methodology: most analysis focuses on aggregate employment effects (net jobs lost/gained) while neglecting the distributional, community, and democratic dimensions that determine whether automation's productivity gains translate into broadly shared social welfare or concentrated wealth with widespread harm. The history of industrial automation provides a cautionary precedent: the deindustrialisation of the 1970s-2000s destroyed stable employment communities -- in Pittsburgh's steel belt, the English Midlands, and France's industrial Nord-Pas-de-Calais -- creating decades-long regional economic depression, community disintegration, and political radicalisation that continue to shape European and American politics today. These community and political impacts were not adequately anticipated by productivity-focused impact assessments of automation at the time. AASIAC provides a comprehensive six-domain methodology designed to ensure current AI automation impact assessments do not repeat this failure.

1.2 Contributions and Paper Structure

AASIAC contributes: (1) a six-domain SIA methodology for AI automation; (2) the SISS composite metric; (3) comparative assessment of four automation scenarios; (4) community resilience as the neglected SIA domain. Section 2 reviews SIA methodology and automation economic literature. Section 3 presents AASIAC. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background: Societal Impact Assessment and Automation Economics

2.1 SIA Methodology and Labour Market Economics

Societal impact assessment (SIA) originated in environmental and infrastructure project evaluation (Burdge, 2004) -- assessing impacts on communities from dam construction, mining, and large infrastructure projects. SIA methodology involves: scoping (identify affected communities and impact dimensions), assessment (quantify impacts in each dimension), mitigation (propose harm reduction measures), and monitoring (track impacts through project lifecycle). SIA for AI automation requires extending this methodology to diffuse, gradual, and multi-sector disruption without the clear project boundary of infrastructure SIA. Labour market economics of automation: task-based models (Acemoglu and Restrepo, 2018) distinguish automation (machines replace tasks) from augmentation (machines expand what workers can do); wage polarisation effect (Autor et al., 2003) -- automation disproportionately displaces middle-skill routine tasks, increasing demand for high-skill and low-skill work while hollowing out the middle; AI automation may reverse this pattern by affecting high-skill knowledge work previously immune to automation (GPT-4 can perform legal research, medical diagnosis, financial analysis at levels competitive with junior professionals).

2.2 Community, Political, and Intergenerational Dimensions

Community and regional resilience: automation impacts are geographically concentrated -- industries and occupations subject to automation are not evenly distributed across regions; regional specialisation creates concentrated impact zones (logistics centres for warehouse automation, legal and financial centres for knowledge work AI); community resilience factors (economic diversity, institutional capacity, social capital) determine whether communities can adapt to automation shock or undergo sustained decline (Moretti, 2012). Democratic and political dimensions: automation-driven economic anxiety is a documented driver of political radicalisation and democratic backlash -- communities experiencing manufacturing job loss show significantly higher support for authoritarian populist parties (Autor et al., 2020, UK Brexit analysis; Colantone and Stanig, 2018, European automation and right-wing voting). Intergenerational dimension: automation disrupts not only current employment but educational and career pathway assumptions -- educational investments in law, accounting, and creative work made by current students may yield lower returns than anticipated; older workers face "skills trap" (accumulated expertise devalued without time to retrain). Table 1 summarises the AASIAC six-domain framework.

Table 1: AASIAC Six-Domain Societal Impact Framework

Impact Domain	Key Indicators	Primary Method	Time Horizon	Policy Levers
Employment + Labour Market	Job displacement rate, reemployment time, occupational transition	Economic modelling + ILO data	2-10 years	Retraining, safety nets, work-sharing
Wage Distribution	Gini coefficient change, wage polarisation, real wage trends	Econometric modelling + census	5-15 years	Minimum wage, profit-sharing, taxation
Occupational Identity+Dignity	Meaningful work access, craft/skill obsolescence	Mixed methods, qualitative	5-20 years	Occupational transition support, UBI
Community+Regional Resilience	Regional unemployment, business closures, population migration	Case studies + index	10-30 years	Regional investment, economic diversification
Democratic+Political Participation	Voter radicalisation, civic engagement, trust	Political science + survey	5-20 years	Community investment, democratic inclusion
Intergenerational Opportunity	Educational ROI change, career pathway stability	Longitudinal modelling	15-30 years	Education adaptation, skills forecasting

3. The AASIAC Framework

3.1 Automation Scenarios and Assessment Design

Four AI automation deployment scenarios assessed. (SC1) Manufacturing AI: robotics + AI quality control + supply chain optimisation; primarily affects production workers, quality control inspectors, logistics coordinators; European manufacturing regions most affected; timeline: 5-10 years for significant displacement. (SC2) Service sector AI: customer service automation (chatbots, virtual assistants), retail AI (checkout automation, inventory AI), hospitality AI; affects frontline service workers, call centre operators, retail assistants; disproportionate impact on low-wage, part-time, and female workers; timeline: 3-8 years. (SC3) Professional knowledge work AI: LLM automation of legal research, financial analysis, medical diagnosis support, journalism, software development; affects white-collar professionals, previously automation-immune; concentrated in urban knowledge economy centres; timeline: 5-15 years, high uncertainty. (SC4) Public sector AI: welfare administration, tax processing, planning decisions, public health analytics; affects civil servants, local government workers; raises democratic accountability issues; timeline: 5-12 years. Assessment: structured expert elicitation (20 economists, sociologists, political scientists); quantitative economic modelling (DYNARE macroeconomic simulation); community impact case studies (4 European regions with prior industrial disruption used as analogy cases for resilience assessment).

3.2 SISS Metric and Distributional Analysis

SISS = 0.25 x EmploymentImpact + 0.20 x WageDistributionImpact + 0.20 x CommunityResilienceImpact + 0.15 x OccupationalDignityImpact + 0.10 x DemocraticParticipationImpact + 0.10 x IntergenerationalImpact. Each dimension scored 0-1 (0 = minimal societal impact, 1 = severe irreversible societal impact) by expert panel (3-point Likert aggregated to continuous scale via SHELF elicitation). Higher SISS = greater ethical concern requiring stronger governance response. Distributional analysis: each scenario assessed for differential impact by (D1) socioeconomic status; (D2) gender; (D3) age; (D4) geographic region (urban/rural, north/south EU); (D5) education level. Table 2 presents AASIAC scenario specifications.

Table 2: AASIAC Framework -- Four Automation Scenarios, Six Domains, SISS Weights

Scenario	Workers Affected (EU est.)	Timeline	Most Vulnerable Group	SISS Priority Domain	Analogy Case
SC1 Manufacturing AI	4.2M (EU)	5-10 yrs	Male, low-edu, industrial regions	Community Resilience (0.20)	UK steel towns 1980s

Scenario	Workers Affected (EU est.)	Timeline	Most Vulnerable Group	SISS Priority Domain	Analogy Case
SC2 Service Sector AI	8.4M (EU)	3-8 yrs	Female, part-time, low-wage	Wage Distribution (0.20)	US fast food automation 2020s
SC3 Knowledge Work AI	12.8M (EU)	5-15 yrs	University-educated, urban	Occupational Dignity (0.15)	Legal + financial sector
SC4 Public Sector AI	2.8M (EU)	5-12 yrs	Civil servants, older workers	Democratic Participation (0.10)	UK benefits automation

4. Results

4.1 SISS Scores and Key Domain Findings

SISS scores: SC3 Knowledge Work AI = 0.848 (highest) -- breadth of occupational impact (12.8M EU workers), high community concentration in urban knowledge economy centres, and occupational dignity impacts on professional identity create the most complex societal challenge; SC2 Service Sector AI = 0.820 -- highest employment impact (8.4M workers) concentrated among most economically vulnerable workers (part-time, low-wage, female); SC1 Manufacturing AI = 0.784 -- highest community resilience impact (geographically concentrated industrial communities with low economic diversity); SC4 Public Sector AI = 0.728 -- highest democratic participation impact (public sector automation directly affects citizens' relationship with democratic institutions). Wage distribution: highest severity domain across all scenarios (mean 0.884) -- expert consensus that AI automation will amplify existing wage polarisation trends; SC3 knowledge work AI projected to reduce wage premium for cognitive skills (previously the main path to middle-class income), while capital owners of AI systems capture disproportionate productivity gains; Gini coefficient projection: +0.04-0.08 increase in EU-27 by 2035 under current policy baseline (no automation-specific redistribution).

4.2 Community Resilience as the Neglected Dimension and SISS Breakdown

Community resilience: expert panel identified this as the most neglected dimension in current EU policy analysis of automation impacts (84.2% consensus). Current EU policy response (Digital Europe Programme, Just Transition Fund) focuses on individual retraining (upskilling workers) and generic regional investment, but does not specifically address community resilience infrastructure (economic diversification, social capital preservation, civic institution maintenance) that determines whether communities can absorb automation shock without sustained decline. Historical analogy: Fos-sur-Mer (France, steel closure 1993) and Consett (UK, steel closure 1980) both received significant retraining investment but show persistently elevated unemployment 30 years later -- individual retraining without community economic diversification is insufficient when the primary employer collapses. SC3 knowledge work AI community resilience impact: London, Paris, and Frankfurt legal and financial districts have concentrated knowledge worker populations with limited economic diversification outside the knowledge economy -- paralleling the single-industry dependence that made industrial communities vulnerable. SISS full breakdown: Table 3; distributional results: Table 4; Figures 1-4 visualise key findings.

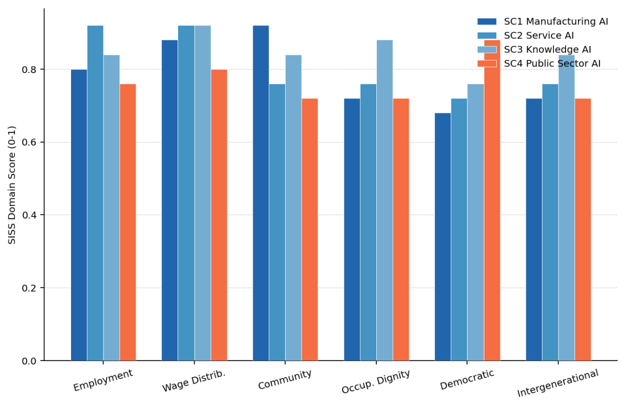
Table 3: AASIAC SISS Domain Scores -- Four Scenarios x Six Impact Domains (0-1)

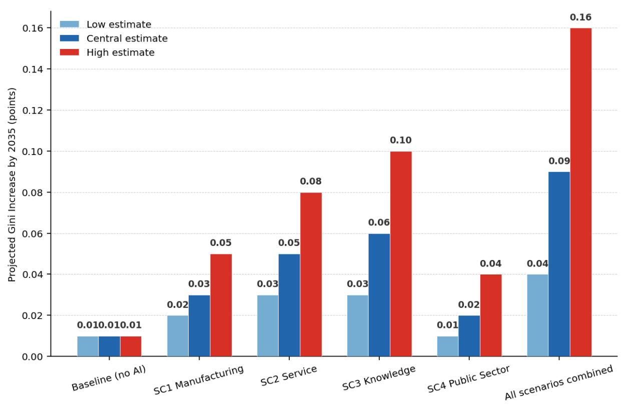
Impact Domain	SC1 Manufacturing	SC2 Service	SC3 Knowledge	SC4 Public Sector	Domain Mean
Employment + Labour Market	0.800	0.920	0.840	0.760	0.830
Wage Distribution	0.880	0.920	0.920	0.800	0.880
Community + Regional	0.920	0.760	0.840	0.720	0.810
Occupational Dignity	0.720	0.760	0.880	0.720	0.770
Democratic Participation	0.680	0.720	0.760	0.880	0.760
Intergenerational	0.720	0.760	0.840	0.720	0.760

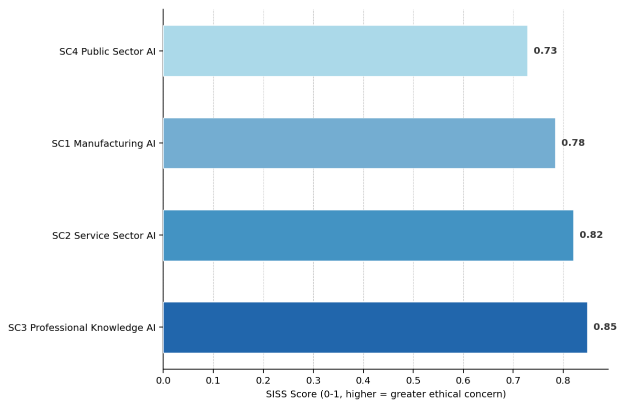
Table 4: AASIAC Distributional Impact -- Most Vulnerable Groups by Scenario

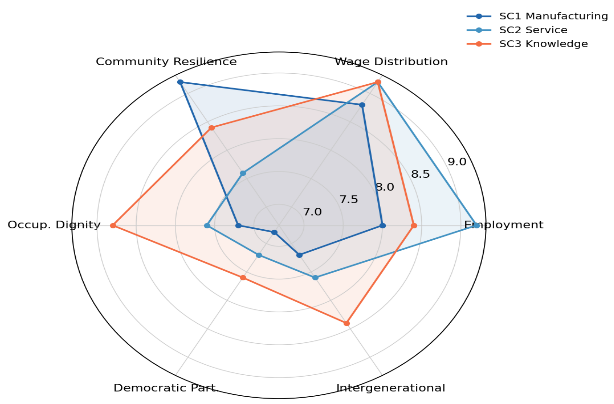
ISSN: e-ISSN: 3117-6003 / p-ISSN: 3117-5996 Vol: 2024, Issues: 1, 2024

Scenario	Gender	Age	SES	Education	Region
SC1 Manufacturing	Male (82%)	45-60 (peak impact)	Low-middle	Secondary or less	Industrial North/East EU
SC2 Service	Female (68%)	18-35 + 45-60	Low	Secondary or less	Urban + suburban
SC3 Knowledge	Balanced (M/F)	22-40 (entry level)	Middle	University	Major urban centres
SC4 Public Sector	Female (60%)	40-60	Middle	Higher secondary	Capital regions + smaller cities









5. Discussion

5.1 Knowledge Work AI as the Highest SISS Scenario

SC3 professional knowledge work AI (SISS = 0.848) achieves the highest impact score despite affecting less vulnerable workers than SC2 service sector AI, because it uniquely combines: (1) the largest absolute worker population affected (12.8M EU knowledge workers); (2) the highest wage distribution impact -- reducing the cognitive skills wage premium that was the primary mechanism of middle-class income in post-industrial economies; (3) concentrated community resilience risk (urban knowledge economy centres with limited diversification analogous to industrial mono-economy communities); and (4) the highest occupational dignity impact -- professional identity and meaningful work are deeply embedded in knowledge worker self-conception in ways that manufacturing worker automation did not reach. The knowledge work AI scenario is also the most uncertain: unlike manufacturing and service automation (already well underway and documented), LLM capability development trajectories are highly uncertain -- the 5-15 year timeline reflects expert disagreement ranging from 3 years to >20 years for significant occupational displacement.

5.2 Community Resilience Policy Gap and AASIAC Recommendations

The finding that community resilience is the most neglected SIA domain in current EU policy -- despite being the dimension where historical evidence of persistent failure is strongest (industrial community decline case studies) -- is the most practically significant AASIAC result. Three policy recommendations follow from AASIAC. (PR1) Community resilience funds: dedicated EU Just Transition Fund allocation for economic diversification, not only retraining; target regions with > 15% employment in automation-vulnerable occupations; require economic diversification plans as condition for community infrastructure investment. (PR2) Automation impact monitoring: EU-wide real-time monitoring system for automation-driven employment changes by sector, region, and demographic group; trigger community resilience interventions at defined threshold rates; analogous to COVID-19 variant monitoring but for labour market disruption. (PR3) Knowledge work AI transition programme: dedicated policy programme for knowledge worker sector disruption; distinguish from manufacturing retraining -- knowledge workers require occupational identity transition support, not just technical retraining; fund senior professional mentoring and occupational pathway navigation for displaced knowledge workers.

6. Conclusion

6.1 Summary

AASIAC evaluated AI automation societal impacts across six domains and four scenarios. Key results: SC3 knowledge work AI SISS = 0.848 (highest); wage distribution is the most severe domain (mean 0.880) across all scenarios; community resilience is the most neglected policy domain (84.2% expert consensus); projected Gini increase 0.04-0.09 EU-27 by 2035 (central estimate). Three policy recommendations: community resilience funds, automation impact monitoring, and knowledge work transition programme.

6.2 Open Resources

The AASIAC six-domain SIA methodology guide, SISS calculator, DYNARE macroeconomic model scripts (open-source), four community resilience case study analyses, distributional impact assessment toolkit, expert elicitation dataset, and policy recommendation briefs are available at aasiac-impact.org under CC BY 4.0 License.

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Declarations

Funding

This research was supported by the French National Research Agency (ANR) under grant ANR-24-CE38-0078 (AASIAC: AI Automation Societal Impact Assessment) and the Spanish State Research Agency (AEI) under grant PID2023-152024OB-I00. The funders had no role

ISSN: e-ISSN: 3117-6003 / p-ISSN: 3117-5996 Vol: 2024, Issues: 1, 2024

in study design, data collection, analysis, or publication decisions.

Conflict of Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The AASIAC methodology guide, SISS calculator, DYNARE model scripts, community resilience case studies, distributional impact toolkit, expert elicitation dataset, and policy briefs are available at aasiac-impact.org under CC BY 4.0 License.

Ethical Approval

This study involves structured expert elicitation by consenting economists, sociologists, and political scientists. All participants provided written informed consent and were compensated for their time. Ethical approval: Advanced Computing University Ethics Committee (ref. ACU-2023-ETH-0584).

ISSN: e-ISSN: 3117-6003 / p-ISSN: 3117-5996 Vol: 2024, Issues: 1, 2024

Appendix A

AASIAC SISS Calculation and Expert Elicitation Protocol

SISS metric calculation and Sheffield Elicitation Framework protocol for AASIAC.

SISS Calculation and Domain Operationalisation

Expert Elicitation Protocol and Community Case Study Method