

Artificial Intelligence, Automation, and the Sustainability of Social Security Systems: The Technological Unemployment Premium Proposal

Semih ERDOĞDU¹

ORCID: 0000-0001-5598-2484

DOI: 10.54752/ct.1968160

Abstract: This study examines the implications of artificial intelligence (AI) and automation for labour markets and the financial sustainability of contribution-based social security systems. Using a qualitative research design based on an integrative literature review and thematic synthesis, the study examines how AI-driven labour displacement may affect contribution-based social security financing. The analysis suggests that automation can generate substantial productivity gains, but may also reduce insured employment and weaken contribution revenues when displacement effects are sufficiently strong and persistent. In response to this financing risk, the study develops the Technological Unemployment Premium, a conceptual mechanism linked to the measurable employment effects of automation rather than to the technology itself. Unlike conventional robot tax proposals and other technology-based financing approaches, the proposed framework links potential

¹ Dr., Sosyal Güvenlik Kurumu (SGK), İzmir Sosyal Güvenlik İl Müdürlüğü, Uzman, İzmir, Türkiye. serdogdu@sgk.gov.tr

DEMİRTAŞ, S., (2026) “Artificial Intelligence, Automation, and the Sustainability of Social Security Systems. The Technological Unemployment Premium Proposal”, Çalışma ve Toplum Sayı: 91, C.4, s.2329-2362

This is an open access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution and reproduction in any medium, provided the original author and source are credited. See <https://creativecommons.org/licenses/by/4.0/>
Makale Geliş Tarihi:10.06.2026 - Makale Kabul Tarihi: 23.09.2026

contribution liability to measurable reductions in insured employment or contribution-generating payroll attributable to automation and outlines preliminary institutional responsibilities, transparent and verifiable assessment criteria, and sector-specific implementation considerations. The study extends the emerging literature on automation and social security financing by showing how a financing response could be tied to measurable labour displacement and the resulting erosion of the contribution base.

Keywords: Artificial intelligence, Social security, Automation, Technological unemployment, Technological Unemployment Premium

Yapay Zekâ, Otomasyon ve Sosyal Güvenlik Sistemlerinin Sürdürülebilirliği: Teknolojik İşsizlik Primi Önerisi

Öz: Bu çalışma, yapay zekâ (YZ) ve otomasyonun işgücü piyasaları ile prim esaslı sosyal güvenlik sistemlerinin finansal sürdürülebilirliği üzerindeki etkilerini incelemektedir. Bütünleştirici literatür taraması ve tematik senteze dayalı nitel bir araştırma tasarımı kullanılan çalışmada, YZ kaynaklı işgücü ikamesinin prim esaslı sosyal güvenlik finansmanını nasıl etkileyebileceği ele alınmaktadır. Analiz, otomasyonun önemli verimlilik artışları sağlayabileceğini; ancak işgücü ikame etkilerinin yeterince güçlü ve kalıcı olması durumunda sigortalı istihdamı azaltabileceğini ve sosyal güvenlik prim gelirlerini zayıflatılabileceğini göstermektedir. Bu finansman riskine karşılık çalışma, teknolojinin kendisinden ziyade otomasyonun ölçülebilir istihdam etkileriyle ilişkilendirilen kavramsal bir mekanizma olarak Teknolojik İşsizlik Primi'ni geliştirmektedir. Geleneksel robot vergisi önerileri ve diğer teknoloji temelli finansman yaklaşımlarından farklı olarak önerilen çerçeve, potansiyel prim yükümlülüğünü otomasyona atfedilebilir sigortalı istihdam veya prime esas kazançlardaki ölçülebilir azalmalarla ilişkilendirmekte ve öncül kurumsal sorumluluklar, şeffaf ve doğrulanabilir değerlendirme ölçütleri ile sektöre özgü uygulama unsurları ortaya koymaktadır. Çalışma, bir finansman mekanizmasının ölçülebilir işgücü ikamesi ve bunun sonucunda prim tabanında meydana gelen aşınmayla nasıl ilişkilendirilebileceğini ortaya koyarak otomasyon ve sosyal güvenliğin finansmanına ilişkin gelişmekte olan literatüre katkı sağlamaktadır.

Anahtar Kelimeler: Yapay zekâ, Sosyal güvenlik, Otomasyon, Teknolojik işsizlik, Teknolojik İşsizlik Primi

Introduction

Artificial intelligence (AI) is increasingly embedded in production processes, labour markets, and economic activity, with growing implications for how work is organised and performed. As AI and automation spread across economic activities, they are changing the allocation of tasks between workers and automated systems, with potentially significant effects on employment, productivity, and the organisation of work (Acemoglu & Restrepo, 2018: 1488–1492; Agrawal et al., 2019: 31–32; Tyson & Zysman, 2022: 256). Social security systems are also under pressure from population ageing, declining fertility, growing health and long-term care needs, and changing labour-market structures (International Social Security Association, 2025). As AI-driven automation continues to transform employment patterns, its implications for contribution-based social security financing will depend in part on whether technological change displaces, complements, or creates employment. Where automation results in a sustained reduction in insured employment, the contribution base may narrow and place additional pressure on the long-term financial sustainability of contribution-based social security systems. Research on automation has traditionally concentrated on employment, wages, productivity, and taxation, but a smaller body of recent work has begun to examine its implications for social security financing more directly. Hötte et al. (2024: 945), for example, show that the effects of automation on tax revenues vary according to the technologies adopted and their stage of diffusion, indicating that fiscal consequences should be assessed dynamically rather than as a uniform outcome of technological change. Wang et al. (2025) go a step further by examining social security contributions themselves. Using data from Chinese manufacturing firms, they find that greater robot exposure reduces both participation in and the amount of corporate social security contributions, with employment displacement and lower wages representing important transmission channels. These findings strengthen the empirical basis for treating the contribution base as a distinct channel through which automation may affect social security financing.

Policy-oriented research has also started to explore alternative ways of financing social security in response to automation. Recent proposals include an employer-paid social security tax on autonomous robots (Casas & Torres, 2026: 69), an Autonomous Social Contribution primarily linked to economic activity and income generated through IoT, AI, cloud computing, and robotics (Cabeçais de Carvalho, 2026), and, in a recent working paper, a Labor Displacement Levy imposed on AI vendors' API and subscription revenues (Turner, 2026). Together, these proposals show that automation is increasingly being discussed as a social security financing issue, although they differ markedly in the basis on which

financial liability is assigned. What remains less developed is an institutional framework that ties potential liability directly to observable and attributable reductions in insured employment or contribution-generating payroll, rather than to autonomous capital, technology-generated activity, or AI-related revenues.

This study focuses on that narrower problem and develops the Technological Unemployment Premium as an employment-outcome-based financing framework for contribution-based social security systems. The proposed mechanism is intended for circumstances in which automation can be associated with measurable and persistent reductions in insured employment or contribution-generating payroll. Unlike technology-based fiscal approaches, it does not impose a financial obligation merely because a firm adopts, owns, or uses automation technology. Instead, potential liability is linked to observable employment-related outcomes and the resulting erosion of the contribution base. The framework is intended to provide a way for contribution-based systems to respond to automation-related financing pressures without taxing technological adoption as such.

The analysis is guided by three research questions. How might AI-driven automation affect insured employment and social security contribution revenues? Under what conditions could these changes create financial pressures for contribution-based social security systems? How might alternative financing arrangements respond to automation-related reductions in the contribution base without directly taxing technological investment?

Drawing on these research questions and the literature reviewed above, the study develops four theoretical propositions. They serve as analytical guides rather than empirically testable hypotheses. The propositions follow the same underlying process but focus respectively on its implications for long-term financial balance, the contribution–benefit relationship, contribution revenues, and possible institutional responses. First, in economies where social security systems rely predominantly on contribution-based financing, persistent automation-induced reductions in insured employment may increase the risk of long-term actuarial imbalances. Second, where AI and automation result in persistent employment displacement, the contribution–benefit balance of social security systems may weaken. Third, the substitution of human labour through AI-driven automation may reduce insured employment and, consequently, social security contribution revenues. Finally, institutional adaptation mechanisms—including alternative financing arrangements and policies addressing automation-induced labour displacement—may help mitigate pressures arising from employment displacement and strengthen the long-term sustainability of contribution-based social security systems.

The study draws primarily on the task-based approach to technological change developed by Acemoglu and Restrepo (2018: 1488–1492; 2019: 3–5). This approach is useful here because it treats the employment effects of automation as the outcome of competing forces, including the displacement of labour from existing tasks and the creation of new tasks. In a contribution-based social security system, these effects also have a financing dimension. Changes in insured employment and labour income affect the contribution base and may therefore influence the financial balance of the system. The theoretical propositions set out above apply this reasoning to the relationship between automation and social security financing.

This study adopts a qualitative research design combining an integrative literature review with thematic synthesis. The integrative review brings together evidence and theoretical insights from different disciplinary and methodological traditions (Whittemore & Knafl, 2005: 546–548; Snyder, 2019: 333–335), allowing research from labour economics, social security, public finance, automation, and taxation to be considered within a common analytical framework. The selected literature was then compared thematically to identify recurring concepts, theoretical arguments, causal mechanisms, institutional challenges, and policy responses relevant to the relationship between technological change and contribution-based social security financing.

The literature was identified through searches of Scopus, Web of Science, Google Scholar, JSTOR, and SSRN. Searches combined terms related to the technological dimension—such as “artificial intelligence,” “automation,” “robotisation,” and “technological unemployment”—with terms related to labour markets and social protection, including “employment,” “labour displacement,” “social security,” “social protection,” “social security financing,” and “robot taxation.” The review focused primarily on studies published between 2010 and 2026, while earlier works were included where they provided relevant theoretical or institutional foundations. Source selection was guided by relevance to the research questions, methodological or theoretical contribution, and the credibility of the publication source. Priority was given to peer-reviewed journal articles, academic books, and reports published by established international organisations. Working papers and other non-peer-reviewed academic studies were included selectively when they addressed recent developments directly relevant to the study, and their publication status was taken into account when interpreting their contribution. Sources were excluded when their substantive focus did not contribute directly to the relationships among automation, labour-market outcomes, social security financing, or alternative financing mechanisms examined in the study. A total of 58 sources were examined during the review process. Of these, 46 were retained for

the final analysis based on their substantive relevance to the research questions and their contribution to the conceptual synthesis. Consistent with the integrative purpose of the review, source selection was based on analytical relevance and contribution to the conceptual synthesis rather than on an exhaustive systematic-review protocol (Whittemore & Knafl, 2005: 546–548; Snyder, 2019: 333–335).

Thematic synthesis was used to organise and interpret the selected literature. Each source was examined in relation to the research questions, with attention to its main arguments, reported labour-market effects, proposed causal mechanisms, implications for social security financing, and suggested policy responses. Recurring ideas and mechanisms were compared across studies and grouped into broader analytical categories. These categories were then refined through repeated comparison of the literature and consolidated into four interrelated themes: (i) technological unemployment and employment displacement, (ii) labour-market transformation and skill polarisation, (iii) implications for contribution-based social security financing, and (iv) policy adaptation mechanisms, including robot taxation and alternative financing models. The themes were used to structure the synthesis and to trace the conceptual relationships linking automation-induced changes in employment to the financing of contribution-based social security systems and, ultimately, to the proposed Technological Unemployment Premium.

An integrative review is particularly suited to the present research problem because it enables the synthesis of insights from different research traditions and bodies of literature (Snyder, 2019: 333–335). This is particularly relevant here because the relationship between automation and social security financing spans several fields that are usually examined separately, including labour economics, social policy, public finance, and robot taxation. The study is concerned with the mechanisms through which automation-related changes in employment may affect contribution-based financing rather than with estimating the magnitude of those effects. Combining an integrative review with thematic synthesis makes it possible to examine these labour-market mechanisms alongside the institutional characteristics of social security financing within a common analytical framework.

The Concept of Social Security

The concept of social security has evolved through a long historical process. Although the term was first introduced in the United States through the Social Security Act of 1935, its modern meaning emerged in response to the profound social and economic transformations brought about by the Industrial Revolution in England. In this context, social security came to encompass the social protection problems generated by industrialisation, the search for solutions to these

challenges, and the institutional measures developed to strengthen systems of social protection (Alper, 2018: 210).

The terms social security and social protection are used in different ways across the literature and institutional contexts. The International Labour Organization (ILO, 2024) generally uses the terms interchangeably, while distinguishing between contributory and non-contributory arrangements within social protection systems (ILO, 2024). The analysis here is limited to contributory social security arrangements in which entitlement and financing are closely linked to insured employment and contribution payments. Non-contributory and tax-financed arrangements fall outside the main scope of the analysis. This distinction is important because the financing mechanism examined in the study operates through changes in insured employment and the contribution base.

Financial sustainability is used here to mean the capacity of a contribution-based social security system to maintain a viable long-term balance between its financing resources and benefit obligations. Particular attention is given to the contribution base, contribution revenues, and the relationship between the number of contributors and the obligations financed through those contributions. This use of the concept is consistent with actuarial approaches that assess the financial position of social security schemes by examining projected contributions, expenditures, and their long-term balance (ILO, 2002). The study does not undertake an actuarial valuation; rather, it examines how automation-related changes in insured employment may place pressure on these components of financial sustainability.

The analysis therefore centres on contributory social insurance, where benefit entitlement and financing are closely connected to insured employment and contribution payments. Such arrangements typically provide protection against risks including old age, disability, unemployment, sickness, maternity, occupational injury, and death, although the specific combination of benefits and financing rules varies across countries (ILO, 2024: 9). Their financial structure is particularly sensitive to changes in the number of insured workers and contribution-generating earnings because these variables directly influence the contribution base from which a substantial share of revenues is collected. The focus is not on the full range of social protection institutions, but on the financing vulnerability of contributory systems when technological change affects insured employment and labour income.

The financing structure of social security varies considerably across countries. In some systems, social contributions linked to employment constitute a major source of financing, whereas others rely more heavily on general government revenues. Recent OECD evidence illustrates the magnitude of this

variation. In 2022, social security contributions accounted for 24.8 per cent of total tax revenues on average across OECD countries, but their share exceeded 40 per cent in Czechia (45.9 per cent), Slovenia (42.8 per cent), and the Slovak Republic (41.6 per cent), while Australia and New Zealand did not levy social security contributions (OECD, 2024b: 23). Immervoll (2024: 5, 13–15) similarly shows that the role of earmarked and contribution-based revenues differs substantially across OECD social protection systems and programmes. The argument is therefore most relevant to systems in which social security financing remains closely tied to insured employment and contribution payments. Predominantly tax-financed systems may be affected by automation through different fiscal channels, which lie outside the main scope of this study.

Across the world, social security systems continue to evolve in response to changing demographic, economic, and social conditions. Governments seek to expand coverage, reduce poverty and inequality, and provide protection throughout the life course. At the same time, declining fertility, population ageing, migration, and urbanisation are placing increasing pressure on pension schemes, healthcare systems, and long-term care services. Population ageing is particularly significant for contribution-based systems because it may simultaneously narrow the relative size of the contributing workforce and increase expenditure pressures associated with pensions, healthcare, and long-term care (OECD, 2024a: 12). Many countries have therefore introduced reforms aimed at strengthening financial sustainability while improving benefit adequacy and access to social protection. Artificial intelligence and automation add a different kind of pressure to these long-standing demographic and fiscal challenges (International Social Security Association, 2025). Unlike demographic pressures, which have been widely recognised for decades, the implications of artificial intelligence and automation for contribution-based social security systems constitute a more recent and still developing area of research. The next section turns to the ways in which technological change may alter the employment relationships on which these systems depend.

Artificial Intelligence, Automation, and the Changing Workforce

Artificial intelligence (AI) has become one of the defining technologies of the digital era, with increasingly significant implications for production, employment, and the organisation of work. Advances in AI and related automation technologies have expanded their application across manufacturing, services, healthcare, transportation, finance, and other economic activities. As their use expands across

production and organisational settings, these technologies may alter task allocation, skill requirements, and demand for different forms of labour. Their labour-market implications depend on the tasks they automate, the activities they complement, and the new forms of work they enable. For contribution-based social security systems, these effects matter because changes in employment and labour income can alter the contribution base on which financing depends.

Artificial intelligence has no single universally accepted definition. In broad terms, it refers to computer systems capable of performing tasks that ordinarily require human intelligence, including reasoning, learning, problem-solving, and decision-making (Boulanin, 2019: 13–14). AI systems use computational methods and algorithms to process information, identify patterns, generate predictions, and support or automate decision-making in tasks that have traditionally required human cognitive capabilities (Nilsson, 1998: 6; Agrawal et al., 2019: 31–32). Advances in machine learning, deep learning, and data-processing capabilities have expanded the range of tasks to which AI can be applied and have facilitated its diffusion across economic activities. As these technologies become more widely integrated into production and organisational processes, they may alter task allocation, skill requirements, and the demand for different forms of labour (Agrawal et al., 2019: 31–32; Tyson & Zysman, 2022: 256).

The rapid advancement of AI and automation technologies is transforming a wide range of economic sectors, including manufacturing, healthcare, retail, transportation, and agriculture. In these settings, automated and AI-enabled systems may substitute for human labour in some tasks while complementing workers in others, depending on the nature of the technology, task structure, skill requirements, and organisational context. This task-level distinction is important because technological adoption does not necessarily translate into proportional reductions in employment; its labour market effects may instead involve a combination of task substitution, worker augmentation, occupational restructuring, and the creation of new activities (Acemoglu & Restrepo, 2019: 3–5; Tyson & Zysman, 2022: 256).

Recent developments in generative AI have broadened the range of tasks potentially affected by automation beyond routine manual work. Language-based systems can now assist with or perform parts of activities such as writing, information processing, translation, customer support, and other knowledge-intensive tasks. This has increased the exposure of some professional and higher-skilled occupations to technological change, although exposure to automation does not necessarily imply the elimination of the corresponding jobs. Evidence from customer-support settings, for example, suggests that generative AI can also

complement workers and raise productivity rather than simply substitute for labour (Eloundou et al., 2024; Brynjolfsson et al., 2025: 889).

AI and robotics should nevertheless be distinguished in terms of the tasks they can affect. AI can automate or support cognitive and service-related tasks without physical automation, whereas robotics is more directly associated with physical tasks and production processes. The distinction is not always clear-cut, since AI and robotics are increasingly combined in production systems. In this study, both are considered within the broader process of automation, while recognising that their effects on tasks, occupations, and sectors may differ.

Alongside these developments in cognitive and knowledge-intensive work, the emergence of Industry 4.0 has further accelerated the integration of digital and automated technologies into production environments. Smart manufacturing systems increasingly combine human labour, robotics, data analytics, and AI-enabled technologies within interconnected production processes. These systems can use production data to support real-time decision-making, operational optimisation, and increasingly autonomous forms of production (Lasi et al., 2014: 239–240). These changes affect not only the tasks performed by workers but also the organisation of production and the skills required in the labour market.

The implications of technological progress for labour demand and wages have attracted considerable scholarly attention. Frey and Osborne (2017: 265) estimate that 47 per cent of US employment is in occupations potentially susceptible to computerisation. Their occupation-based approach generated substantial debate and was followed by studies adopting task-based methodologies, which generally produced lower estimates of automation risk. Arntz et al. (2016: 4), for example, estimate that around 9 per cent of jobs across OECD countries are highly automatable when differences in the tasks performed within occupations are taken into account. These contrasting estimates demonstrate that automation-risk projections are highly sensitive to methodological assumptions and should not be interpreted as direct forecasts of future job losses. Nevertheless, the literature indicates that AI and automation may substantially reshape the task content and occupational structure of employment, even where aggregate employment effects remain uncertain (Frey & Osborne, 2017: 265; Arntz et al., 2016: 4).

Acemoglu and Restrepo (2018: 1488–1492) provide a theoretical framework for understanding the competing effects of automation on labour demand. Their analysis shows that automation may generate productivity gains while simultaneously displacing labour from tasks previously performed by workers, so that its overall employment effect depends on the balance between these forces. Empirical evidence from the United States subsequently provided by Acemoglu and Restrepo (2020: 2188) shows that greater exposure to industrial robots was

associated with reductions in employment and wages in affected local labour markets. This contrast helps distinguish the theoretical possibility of labour displacement from the employment effects observed in particular institutional and sectoral settings.

AI and automation may reshape employment patterns, wage structures, and job quality in uneven ways. Although technological progress can enhance productivity, it may also increase the exposure of certain routine and lower-skilled tasks to automation. Tyson and Zysman (2022: 256) emphasise that the labour-market effects of AI and automation are likely to be unevenly distributed, with particularly important implications for employment polarisation, job quality, and income inequality. Research on employment polarisation shows a similar pattern, with some middle-skill occupations contracting while employment growth becomes more concentrated at the upper and lower ends of the occupational distribution (Autor et al., 2006: 189–190; Goos et al., 2014: 2509). Peetz (2019), in his analysis of the Australian labour market, similarly identifies the dual effects of digitalisation: the disappearance of some occupations alongside the creation of new ones. His findings indicate a gradual erosion of middle-skill employment, accompanied by growth at both the lower and upper ends of the labour market. The expansion of platform-based business models has further contributed to the spread of more flexible and potentially precarious forms of employment.

Evidence from China further illustrates that the employment effects of industrial robots need not be uniformly negative. Using firm-level data, Zhang et al. (2023: 787) find that the adoption of industrial robots is associated with an increase in firm-level employment. The authors attribute this result primarily to output expansion, productivity improvements, and product upgrading, while also identifying skill-biased effects and spillovers through production networks. The Chinese evidence is a useful reminder that direct labour displacement is only one part of the employment effect; productivity and scale effects may generate compensating demand for labour. For contribution-based social security systems, what matters is the net effect of these forces on insured employment and contribution-generating earnings.

Research on the future of work also highlights the challenges that digitalisation and the growth of non-standard forms of employment may create for social security systems (Behrendt et al., 2019: 17). Evidence from developing countries further suggests that AI-driven labour-market transformation may create additional challenges for the coverage, financing, and effectiveness of social protection systems, reinforcing the need to consider reforms aimed at improving their inclusiveness and long-term resilience (Virgilio et al., 2024).

The fiscal implications of automation for welfare states depend in part on how technological change affects employment, earnings, and the contribution base. Where displacement effects persist and are not offset by new employment opportunities or other compensating effects, contribution-based systems may face additional financing pressures. How social security institutions respond to changing employment structures will also influence the scale of these financing pressures.

Acemoglu and Restrepo (2019: 3–5) provide a useful framework for interpreting these countervailing effects. Their task-based approach distinguishes between a displacement effect, arising when automation replaces labour in previously human-performed tasks, and a reinstatement effect, arising from the creation of new tasks in which labour has a comparative advantage. Productivity gains from automation may also increase labour demand in non-automated activities. The overall effect on employment therefore depends on the relative strength of displacement, reinstatement, and productivity effects. For social security financing, the critical case is one in which displacement effects remain strong and persistent enough to reduce insured employment and the contribution base.

AI, automation, and digital platforms are also changing the form of employment itself. The digital economy has facilitated the growth of new and more flexible forms of work, including platform-based employment and gig work, which may not fit easily within social security arrangements designed around standard employment relationships. These changes can create gaps in social protection coverage and complicate contribution collection where eligibility and financing remain closely tied to conventional employment status and wage-based contributions (Behrendt et al., 2019: 17).

Financing of Social Security Systems

The provision of social security depends on effective institutional arrangements as well as sustainable and sufficiently diversified financial resources. Social security systems redistribute resources across individuals and generations to provide protection against recognised social risks, and their ability to do so depends on maintaining a viable balance between revenues and expenditure obligations. The way social security is financed is therefore central to its long-term sustainability and to the ability of welfare states to maintain adequate and broad-based coverage.

Social security systems are financed through different combinations of social insurance contributions, general government revenues, and other public resources, with the relative importance of these sources varying across countries and

programmes. In contributory schemes, payments by insured workers and employers constitute a central source of revenue and are generally linked to legally defined social insurance entitlements. General government revenues may complement these contributions through subsidies, transfers, or other forms of public financing designed to support coverage and address financing gaps. The balance between contribution-based and tax-financed resources reflects the institutional design, redistributive objectives, and fiscal characteristics of individual social security systems (ILO, 2024).

The revenue structure of social security systems may also include earmarked taxes and other programme-specific sources in addition to conventional social insurance contributions and general government transfers. OECD evidence shows that the composition of these financing sources varies substantially across countries, reflecting differences in institutional design and the extent to which revenues are earmarked for particular social protection programmes (Immervoll, 2024: 13–15; OECD, 2024b: 33). In many OECD countries, social security contributions remain the predominant form of earmarked financing for social security-type benefits, although other earmarked taxes and non-tax contributions also play a role in some systems. This variation matters because the financial effects of automation depend partly on how heavily a social security system relies on employment-related contributions. The analysis focuses on the contribution-financing channel without assuming that technological change affects all social security systems through the same fiscal mechanism.

Greater use of general government revenues is another possible response to a persistent weakening of employment-related contribution revenues. This would make social security financing less directly dependent on insured employment, although it would also increase its reliance on general taxation and public budgets. The balance between these sources is likely to differ across countries according to their existing financing arrangements and fiscal conditions. Since the present study is concerned specifically with contribution-based systems, the analysis focuses on adaptation within this financing structure rather than on a broader transition towards predominantly tax-financed social security.

Contribution-based social security systems must balance the need for sustainable financing with their redistributive and protective objectives. Reforms to contribution structures therefore need to consider their financial effects without undermining the broader functions of social security (Goudswaard & Caminada, 2015).

The financial sustainability of social security systems depends on a combination of demographic, labour-market, and institutional factors. Population ageing may increase expenditure pressures, while changes in employment

structures, informality, and non-standard forms of work can affect the size and composition of the contribution base. Policy responses have included efforts to broaden coverage, strengthen labour-market participation, improve contribution collection, and diversify the financial resources available to social protection systems. Automation adds another dimension to this debate because it may alter both the level and composition of contribution-generating employment, raising questions about how contribution-based systems should adapt their financing structures (Díaz & Grau Ruiz, 2020: 340).

For contribution-based systems, these pressures become financially significant when they affect expenditure obligations or the revenues generated through insured employment. The revenue channel is particularly important for the present analysis. Where social security revenues depend heavily on employment-related contributions, persistent reductions in insured employment or contribution-generating earnings may weaken the revenue base from which benefits are financed. AI and automation may create additional financing pressure when their displacement effects are sufficiently strong and persistent to reduce contribution-generating employment.

Social Security Contributions

Social security contributions are compulsory payments made by insured workers, employers, or both to finance contributory social security schemes in accordance with national legislation. They are typically calculated by applying specified contribution rates to wages, earnings, or other legally defined contribution bases, although their design varies across countries and social insurance branches. From an economic perspective, employer and employee contributions form part of the broader cost of employment and are sometimes treated in the literature as deferred or indirect wages (Korkusuz & Uğur, 2010: 182; Şakar, 2017: 63). From a legal and public-finance perspective, social security contributions have also been described as tax-like because they are compulsory payments established by law and used to finance collectively organised social protection (Talas, 1983: 359; Tuncay & Ekmekçi, 2015: 136; Dilik, 1992: 219; Korkusuz & Uğur, 2010: 185). In this sense, social security contributions may also be regarded as parafiscal revenues, since they are compulsory payments earmarked for the financing of specific social protection purposes rather than general public expenditure.

Contributory arrangements also support risk pooling and solidarity by linking collective financing to access to social security benefits. Contribution rates and financing arrangements vary across countries and social insurance branches, reflecting differences in institutional design, labour-market conditions, and national

policy choices. Recent evidence does not support the general assumption that social security contributions are a major determinant of employment or informality, nor does it suggest that lower contribution rates necessarily produce substantial gains in employment or formalisation (Calligaro & Cetrángolo, 2023: 1). An adequate contribution base remains important for the financial capacity of contributory social security systems, while contribution arrangements need to reflect national labour-market and institutional conditions.

Digital technologies, artificial intelligence, and robotics may change employment structures and reduce labour demand for certain tasks and occupations, but their aggregate employment effects remain uncertain and may differ across sectors and groups of workers. This uncertainty matters for contribution-based social security systems because their revenues remain closely tied to insured employment and contribution-generating earnings. If automation leads to persistent reductions in insured employment or labour income, the contribution base may weaken and place additional pressure on social security financing. Firm-level evidence from China provides direct support for this channel: greater exposure to industrial robots is associated with lower participation in social security contributions and smaller contribution payments, partly through employment displacement and wage effects (Wang et al., 2025). Productivity and scale effects may offset some of these pressures if they support employment, wages, or other sources of public revenue. The fiscal consequences of automation depend on its net labour-market effects and on how the social security system is financed; they are not an inevitable consequence of technological adoption (OECD, 2024a: 14).

Automation and the Financial Sustainability of Contribution-Based Social Security Systems

The implications of artificial intelligence and automation for contribution-based social security systems depend fundamentally on how technological change affects insured employment and contribution-generating earnings. Automation may substitute for human labour in some tasks and occupations while complementing labour, increasing productivity, and generating new employment opportunities in others. Existing evidence does not support the assumption that technological change necessarily leads to aggregate job destruction, and its effects may differ substantially across sectors, occupations, and groups of workers (Acemoglu & Restrepo, 2018: 1488–1492; Arntz et al., 2016: 4; OECD, 2024a: 14). These uneven effects matter for contribution-based social security systems because persistent displacement or wage losses among affected workers may weaken contribution

revenues even when aggregate employment remains relatively stable. The central question is not whether automation inevitably reduces employment, but when its labour-market effects become strong and persistent enough to erode the contribution base on which social security financing depends.

The labour-market effects of AI also depend on which tasks and decisions are affected by technological adoption. Agrawal et al. (2019: 31–32) conceptualise advances in machine learning primarily as improvements in prediction technology and show that automated prediction may either facilitate the automation of particular decisions or complement human judgement. AI adoption should not, in itself, be equated with labour displacement. For contribution-based social security systems, financing pressures arise when technological change produces sufficiently persistent reductions in insured employment or contribution-generating earnings.

Recent empirical work provides more direct evidence of a link between automation and social security contribution revenues. Using nationally representative tax survey data from Chinese manufacturing firms, Wang et al. (2025) find that greater exposure to industrial robots significantly reduces both firms' participation in social security contributions and the amount of contributions paid. Their analysis indicates that these effects operate partly through reductions in labour demand and average wages, with stronger effects observed among small, private, labour-intensive, and non-high-tech firms. These findings come from Chinese manufacturing and cannot be assumed to apply in the same way across other institutional settings. They nevertheless provide empirical evidence for the mechanism examined here: when automation reduces employment or labour income, contribution-based social security revenues may also decline (Wang et al., 2025).

Digital transformation may also strengthen the administrative capacity of social security institutions. Technologies such as artificial intelligence, data analytics, and digital service platforms can support more efficient administration, improve access to services, and enhance the capacity of institutions to identify coverage gaps and respond to changing patterns of work (UNU-EGOV, 2023: 1–2). Technological change therefore presents a mixed picture for social security. Digitalisation may create financing challenges by reshaping labour markets, while at the same time giving institutions new tools to improve the administration and delivery of social protection.

Recent theoretical research provides a nuanced assessment of robot taxation as a policy response to automation. Guerreiro et al. (2022: 279) show that robot taxation may be optimal during a transitional period in which routine workers exposed to automation have limited opportunities to move into non-routine occupations, but that the optimal tax falls to zero once these workers retire.

Costinot and Werning (2023: 2261) similarly demonstrate that distributional concerns can justify non-zero taxes on robots, while the optimal magnitude of such taxes may decline as automation becomes more extensive. Thuemmel (2023: 1154) further shows that the appropriate tax treatment of robots depends on their relative cost, the distributional consequences of automation, and the availability of alternative fiscal instruments; when labour-income taxation can also be adjusted, the additional welfare gains from taxing robots differently from other equipment capital may be limited. The common implication is that there is no universally optimal way to tax automation: the appropriate response depends on labour-market adjustment, distributional consequences, and the broader configuration of the tax system (Guerreiro et al., 2022: 279; Costinot & Werning, 2023: 2261; Thuemmel, 2023: 1154).

Recent research has brought the relationship between automation and social security financing more directly into the policy debate. Casas and Torres (2026) examine alternative tax instruments for preserving social security contributions in a pay-as-you-go system under increasing automation and find that an employer-paid social security tax on autonomous robots may constitute an efficient long-run response. Cabeçais de Carvalho (2026) proposes an Autonomous Social Contribution linked to the economic value generated through IoT, artificial intelligence, cloud computing, and robotics, with the contribution levied through mechanisms associated with technology-generated income, services, or assets. A recent working paper by Turner (2026) similarly links AI-driven labour displacement to payroll-tax erosion and proposes a Labor Displacement Levy on AI vendors' API and subscription revenues, with the proceeds directed towards social security and workforce-transition programmes. These proposals place social security financing more clearly within the automation debate, but they differ in the basis on which fiscal liability is assigned. These approaches primarily attach financial obligations to autonomous capital, technology-generated economic activity, or AI-related revenues. The Technological Unemployment Premium takes a different approach: potential liability is triggered by evidence of measurable and persistent reductions in insured employment or contribution-generating payroll attributable to automation. Its distinctive feature lies not in the general proposition that automation may require an additional source of social security financing, but in linking potential contribution liability to observable employment outcomes and the resulting erosion of the contribution base.

The emerging literature shows that the case for automation-related fiscal measures—and their appropriate design—depends on the tax base, institutional purpose, distributional effects, and relationship to observed labour-market outcomes. A narrower question remains: how should a contribution-based social

security system respond when automation is associated with measurable and persistent reductions in insured employment and the contribution-generating payroll on which its financing depends? The proposed mechanism approaches this problem by shifting the focus from technological adoption itself to its observable employment consequences.

The South Korean experience provides a useful illustration of the difficulties involved in designing technology-based fiscal measures. Rather than introducing a direct tax on robots, South Korea reduced tax incentives for investments in automation technologies, thereby increasing the relative tax cost of such investments. This policy has subsequently been characterised in the literature as a form of “quasi-robot tax” because the fiscal burden operates through the treatment of automation investment rather than through a direct levy on robots themselves (Kang et al., 2024: 1; Holtmann et al., 2025: 1). Empirical evidence from the Korean reform indicates that reductions in automation-related tax credits can discourage automation investment and affect firms’ employment decisions (Kang et al., 2024: 1; Holtmann et al., 2025: 1). For the present argument, the key distinction is that the Korean approach links fiscal treatment to investment in automation rather than to the observable employment consequences of that investment. A firm may face less favourable tax treatment even when its automation investment produces no measurable reduction in insured employment or the social security contribution base. This creates a clear rationale for considering an outcome-based mechanism that links potential liability to attributable employment displacement rather than to technological investment itself.

The robot-tax literature and the South Korean experience point to a common problem: measures tied directly to automation can affect firms regardless of whether technological adoption actually reduces insured employment. The Technological Unemployment Premium approaches this problem differently. Unlike conventional robot-tax proposals, it is not triggered simply by the acquisition, ownership, or use of automation technology. Potential liability instead depends on measurable and persistent reductions in insured employment attributable to automation and on the resulting erosion of the social security contribution base. The aim is to preserve a degree of technological neutrality while creating a financing response to identifiable losses in contribution-generating employment. The proposal is designed specifically for contribution-based social security systems and is presented as a conceptual framework for institutional adaptation, not as a fully specified tax instrument.

Operational Framework of the Proposed Mechanism

The Technological Unemployment Premium is conceived as an employer-side social security contribution that could operate within existing contribution systems rather than as a separate tax on robots or technological capital. Its potential liability would fall on the employer or firm whose use of automation is found to have contributed materially to a measurable and sustained reduction in contribution-generating employment. The adoption of AI or automation would not, by itself, trigger such an obligation. Establishing liability would require more than a simple comparison of employment levels before and after automation. The assessment would consider the timing and intensity of automation, changes in insured employment and contribution-generating payroll, shifts in occupational or task composition, productivity changes, and sector-specific employment trends. Where suitable data are available, sectoral or firm-level counterfactual benchmarks could help distinguish automation-related displacement from employment changes caused by business cycles, firm-specific shocks, restructuring, or other non-technological factors. Potential liability would therefore be assessed on the basis of several related indicators rather than determined by a fixed formula. Although the precise legal classification of the premium would depend on national social security and tax law, its intended economic function is to offset part of the contribution revenue lost through attributable labour displacement.

Implementing such a mechanism would require coordination among several public institutions. Social security authorities could assess changes in contribution-generating employment and contribution revenues and, where the relevant conditions are met, determine premium liabilities. Labour ministries and labour inspectorates could contribute to assessing whether workforce reductions are materially associated with automation, while tax authorities and national statistical agencies could provide relevant data on employment, payroll, productivity, and investment in automation. The division of these responsibilities would depend on each country's institutional structure and administrative capacity. Such coordination would allow assessments to draw on multiple sources of verifiable evidence rather than relying solely on administrative judgement.

Applying the premium would require predefined evidentiary thresholds; technological adoption alone would not be sufficient. A premium obligation should arise only where the available evidence indicates a sustained and material deterioration in contribution-generating employment that is plausibly linked to labour substitution through automation. The assessment should consider the relevant indicators collectively rather than treating any single variable as sufficient to establish liability. Considering the indicators together would reduce the risk of

attributing employment losses caused by cyclical downturns, firm-specific restructuring, changes in demand, or other non-technological factors to automation. The precise thresholds and weighting of the indicators would need to be calibrated empirically and adapted to national institutional and sectoral conditions before the mechanism could be implemented in practice.

Initial implementation could focus on sectors with comparatively high exposure to automation and greater potential for labour substitution. Sectoral eligibility should not, however, rest solely on broad industry classifications, since the nature and employment effects of automation may vary substantially across firms, occupations, and tasks within the same sector. Bringing a particular industry within the scope of the mechanism would therefore require evidence on its automation intensity, occupational structure, labour intensity, and observed changes in contribution-generating employment. Sectors or activities in which automation primarily complements labour rather than substitutes for it may require different assessment criteria or remain outside the initial scope of the mechanism. A gradual rollout would allow the indicators and evidentiary thresholds to be tested and recalibrated across different production structures before wider implementation.

Premium liability and the amount payable should be determined in separate stages. Liability would first be assessed using transparent and verifiable indicators. Indicators such as changes in insured employment, reductions in contribution-generating payroll, automation intensity, productivity changes associated with labour substitution, firm size, and sector-specific conditions could be used to assess whether the evidentiary threshold for liability has been met. Once liability is established, the premium amount could be linked to the estimated loss of contribution-generating payroll or social security contribution revenues associated with the identified employment displacement, subject to nationally defined parameters, ceilings, and adjustment rules. This would link the financial obligation directly to the financing pressure created by the identified employment displacement rather than impose a uniform charge on technological investment. The present study does not specify a numerical premium rate or calculation formula. These parameters would require empirical calibration using firm-level data on employment, payroll, automation, and contributions within the relevant national and sectoral context.

Under the proposed framework, the additional liability would fall on the employer whose automation-related restructuring is found to have produced a measurable and attributable reduction in contribution-generating employment. No additional contribution would be imposed directly on affected workers, since doing so would shift part of the financing burden to those whose employment position

may already have been adversely affected by technological change. The state would retain its existing role in the financing and administration of the social security system rather than being assigned a fixed matching contribution under the proposed mechanism. This does not preclude governments from supporting employment-transition or reskilling programmes through general revenues, but such support would remain institutionally separate from the premium itself.

The Technological Unemployment Premium should also be distinguished from conventional unemployment insurance contributions. Unemployment insurance contributions are generally collected on an ongoing basis within the ordinary employment relationship and finance protection against the broader risk of unemployment. The proposed premium, by contrast, would arise only when a specific and attributable erosion of contribution-generating employment is linked to automation. Its purpose is therefore not to insure workers against unemployment in general, but to respond to a particular loss in the social security contribution base associated with technological substitution.

Consistent with this distinction, revenue from the Technological Unemployment Premium would primarily address the social security and labour-market consequences of automation-induced displacement. Its primary function would be to offset, at least partially, the loss of contribution revenue associated with measurable reductions in contribution-generating employment. After this primary financing function is taken into account, and depending on national institutional arrangements, part of the revenue could also support unemployment protection, active labour market policies, vocational reskilling, and lifelong learning programmes for workers affected by technological displacement. Earmarking the revenue for these purposes would maintain a clear link between the premium and the employment and social security consequences it is intended to address. The premium is thus conceived as a complementary financing instrument within the social insurance system, not as a general tax on technological development.

These elements define the institutional logic of the proposed mechanism without prescribing a uniform administrative model or contribution formula. Its practical design—including attribution methods, evidentiary thresholds, assessment periods, contribution rates, and institutional responsibilities—would need to reflect national labour-market conditions, social security legislation, administrative capacity, and data availability. The framework therefore identifies the main components of an employment-outcome-based financing mechanism while leaving their empirical calibration and country-specific design to future research.

Conceptual Advantages of the Technological Unemployment Premium

One of the main strengths of the proposed framework is its outcome-based structure. Unlike fiscal measures imposed directly on robots, automated capital, or technology-related revenues, the Technological Unemployment Premium relates potential liability to the employment consequences of automation. This brings the financing mechanism closer to the specific problem it is intended to address: erosion of the contribution base associated with automation-related labour displacement.

The framework may also fit more readily within existing social security institutions. Because the mechanism is framed as an additional social security contribution rather than a general tax on technological capital, it could in principle operate through existing contribution-collection structures. Social security institutions already maintain administrative systems for registering insured workers, recording contribution-generating earnings, and collecting employer contributions. These arrangements could provide part of the institutional infrastructure needed for an employment-outcome-based mechanism, although implementation would still require additional data, attribution procedures, and coordination with labour-market and tax authorities. How well the mechanism fits existing institutions would vary across countries according to their administrative and legal frameworks.

Its outcome-based design also gives the framework a degree of technological neutrality. The proposed premium would not differentiate among particular technologies or impose liability simply because a firm invests in robotics, artificial intelligence, or other forms of automation. The assessment would instead focus on the employment consequences of technological adoption. Firms whose investments increase productivity without producing attributable reductions in insured employment would fall outside the intended scope of the mechanism. This outcome-based design may be less likely to discourage productive technological investment than measures imposed directly on automation technology itself. The relevant distinction is therefore not that the premium would leave employer costs unchanged, but that additional liability would arise only where automation is associated with an identifiable loss in contribution-generating employment. It does not eliminate behavioural or investment effects altogether, since additional liability associated with employment displacement could still influence firms' decisions. The magnitude and direction of these effects would depend on how the premium is designed and calibrated and would need to be assessed empirically.

Practical Challenges and Implementation Considerations

The most difficult implementation issue is likely to be attribution. Employment reductions observed after the adoption of automation may also reflect changes in product demand, outsourcing, organisational restructuring, macroeconomic conditions, or other firm-specific factors. Establishing that a reduction in insured employment or contribution-generating payroll is attributable to technological substitution would require a credible counterfactual assessment rather than a simple before-and-after comparison. This matters because attribution is a core condition for potential liability under the proposed framework. Without sufficiently reliable procedures for distinguishing automation-related displacement from other causes of employment change, the mechanism could impose liabilities that do not correspond to the contribution-base erosion it is intended to address. Future empirical research could examine this attribution problem using difference-in-differences designs, comparisons with matched firms that have not adopted similar automation technologies, or sector-level counterfactual benchmarks. These approaches could help assess whether observed changes in insured employment or contribution-generating payroll differ from those that would likely have occurred in the absence of automation.

Attribution also creates substantial data and administrative demands. Existing social security contribution systems may provide part of the necessary institutional infrastructure, but conventional contribution records alone would not be sufficient to establish automation-related displacement. Implementation would require reliable information on employment and payroll changes, the timing and nature of automation investments, occupational or task-level restructuring, and other factors capable of explaining changes in labour demand. Effective administration would also require data-sharing and coordination among social security institutions, tax authorities, labour-market agencies, and other relevant public bodies. These requirements may be particularly demanding in jurisdictions where administrative data are fragmented or where institutional capacity for firm-level assessment is limited.

A further difficulty is that the employment effects of automation vary across sectors and firms. Similar technologies may produce different employment outcomes depending on production structures, workforce composition, firm size, competitive conditions, and the extent to which automation substitutes for or complements existing labour. A uniform threshold or contribution formula could produce uneven or unintended effects across sectors and firms. Sector-specific benchmarks or adjustment parameters may be needed to account for these differences. Greater differentiation, however, would increase administrative

complexity and create additional boundary and classification problems. The appropriate degree of sectoral differentiation would therefore need to be determined empirically rather than *a priori*.

The mechanism must also balance the need to strengthen social security financing against the risk of discouraging productivity-enhancing technological investment. Although the mechanism does not impose liability directly on the acquisition or use of automation technology, firms may still anticipate additional costs when technological adoption is expected to displace workers. The premium could consequently influence decisions about automation, workforce composition, outsourcing, and the timing or location of investment. These responses would depend on the contribution rate, attribution rules, exemptions, assessment period, and availability of alternative production arrangements. Excessively high or poorly calibrated liabilities could discourage productivity-enhancing investment or prompt firms to reorganise employment to avoid the premium. The framework's relative technological neutrality is best understood as a design objective, not as an assumption that behavioural distortions can be eliminated.

These challenges make clear that the Technological Unemployment Premium remains a conceptual policy framework that requires empirical validation before practical implementation can be considered. Its practical feasibility would depend on the availability and quality of firm-level data, the reliability of methods used to identify automation-related employment effects, the administrative capacity of relevant institutions, and the empirical calibration of liability thresholds and premium parameters. Pilot implementation and subsequent evaluation would be needed to determine whether the mechanism can generate meaningful additional financing without creating disproportionate administrative burdens or unintended effects on employment, investment, and technological adoption. Future empirical research should test these relationships across different sectors and institutional settings before broader implementation is considered.

Conclusion

Artificial intelligence and automation are reshaping labour markets in ways that may have important implications for the financing of contribution-based social security systems. This study examined how AI-driven labour displacement could affect insured employment, labour income, and the contribution base on which these systems depend. The literature shows that the employment effects of automation are neither uniform nor predetermined: technological change may replace labour in some tasks and occupations while complementing workers, creating new tasks, or supporting productivity and employment elsewhere. Its

implications for social security financing therefore depend on whether these changes lead to persistent reductions in insured employment or contribution-generating payroll. The four theoretical propositions developed in the study reflect these conditional relationships and serve as analytical expectations that guide the assessment rather than as empirically tested hypotheses.

The study contributes to an emerging literature on the implications of automation for social security financing. While much of the existing research has focused on employment, wages, inequality, productivity, and optimal taxation, recent studies have examined more directly how automation may affect social security financing and how alternative contribution or taxation mechanisms might respond (Casas & Torres, 2026: 69; Cabeçais de Carvalho, 2026; Turner, 2026). These approaches assign financial obligations on different bases, including autonomous capital, technology-generated economic activity, and AI-related revenues. The contribution of this study lies not in claiming that the relationship between automation and social security financing has previously been overlooked, but in developing an employment-outcome-based framework in which potential liability is tied to measurable, persistent, and attributable reductions in insured employment or contribution-generating payroll associated with automation. The contribution base thus becomes the main transmission channel through which automation-induced labour displacement may create financing pressures for social security systems.

The Technological Unemployment Premium develops this idea into a more specified conceptual framework for alternative financing. Its contribution lies in linking potential liability to employment outcomes associated with automation while also addressing the institutional and evidentiary conditions under which such liability might be assessed. The framework separates the determination of liability from the calculation of the amount payable and recognises the need for sector-specific calibration and adaptation to national conditions. These features do not establish the practical feasibility or effectiveness of the mechanism, but they provide a basis for subsequent empirical testing and policy development.

The framework remains conceptual rather than prescriptive and is subject to several limitations. This study does not empirically validate the mechanism, estimate premium rates or fiscal effects, or examine how firms might respond to its introduction. A particularly difficult empirical issue is separating employment and contribution losses associated with automation from those caused by economic cycles, changes in demand, organisational restructuring, outsourcing, or other firm- and sector-specific factors. The indicators and counterfactual benchmarks proposed in the framework may assist this assessment, but their reliability and practical applicability need to be tested. Differences in automation intensity,

labour-market structures, social security financing arrangements, administrative capacity, and data availability also limit the framework's direct generalisability across countries and sectors. Future research should therefore examine the relationship between automation exposure, insured employment, contribution-generating payroll, and contribution revenues using firm-level or sectoral data. Simulation and microsimulation models could then be used to evaluate alternative premium designs and their fiscal and behavioural effects, while comparative studies could assess how the mechanism might operate under different social security and institutional arrangements.

The broader policy question is how contribution-based social security systems can adapt when technological change alters the employment relationships on which their financing depends. If automation produces persistent reductions in insured employment or contribution-generating payroll, these systems may require financing arrangements that are less vulnerable to a narrowing contribution base. Greater reliance on general government revenues represents one possible response, although the appropriate balance between contribution-based and tax-financed resources will depend on national institutional and fiscal conditions. Within contribution-based systems, the Technological Unemployment Premium developed here represents a more targeted response to automation-related erosion of the contribution base. It is not intended to replace existing labour-market or social protection policies. Its relevance ultimately depends on whether automation-related employment losses can be identified with sufficient reliability and whether additional financing can be generated without imposing disproportionate costs on productive technological investment.

Artificial intelligence and automation raise questions that extend beyond employment and productivity to the institutional foundations of social protection financing. For contribution-based social security systems, the central concern is not technological change itself, but whether persistent labour displacement weakens the insured employment and contribution-generating payroll from which revenues are derived. The Technological Unemployment Premium developed in this study provides a conceptual framework for considering how these systems might respond when such pressures arise. It is not presented as a definitive solution, and its feasibility, effectiveness, and broader economic effects remain to be established empirically. The wider challenge for social policy is to ensure that the financing of social security can adapt as the relationship between technology and labour changes.

Geniřletilmiř Trke zet

Bu alıřma, yapay zekâ ve otomasyonun iřgc piyasalarında yarattığı dnřmn prim esaslı sosyal gvenlik sistemlerinin finansal srdrlebilirliğine nasıl yansiyebileceğini incelemektedir. İncelemenin odağında, sigortalı istihdam ile prime esas kazançların azalması durumunda ortaya ıkabilecek finansman baskıları bulunmaktadır. alıřma  soruya yanıt aramaktadır: Yapay zekâ kaynaklı iřgc ikamesi sigortalı istihdamı ve sosyal gvenlik prim gelirlerini nasıl etkileyebilir? Bu deėiřimler hangi kořullarda prim esaslı sistemlerde mali baskı oluřturabilir? Alternatif finansman dzenlemeleri, teknolojik yatırımları doėrudan vergilendirmeden otomasyonla iliřkili prim tabanı kayıplarına nasıl karřılık verebilir? Analizin kapsamı, hak kazanma ve finansmanın sigortalı alıřma ile prim demelerine baėlı olduėu dzenlemelerle sınırlıdır. Prim gerektirmeyen ve genel vergilerle finanse edilen dzenlemeler temel inceleme alanının dıřında tutulmaktadır.

Kuramsal deėerlendirme, teknolojik deėiřimin istihdam zerindeki etkilerini grevler zerinden ele alan yaklařıma dayanmaktadır. Otomasyon, alıřanların yerine getirdiėi bazı grevleri devralırken verimlilik artıřı saėlayabilir ve insan emeėinin tamamlayıcı rol stlendiėi yeni grevlerin oluřmasına katkıda bulunabilir. Dolayısıyla teknolojik ilerlemenin toplam istihdam zerindeki etkisi nceden belirlenmiř deėildir. alıřmada geliřtirilen drt kuramsal nerme, bu kořullu iliřkiyi sosyal gvenlik finansmanına tařıtmaktadır. nermeler sırasıyla uzun vadeli akteryal dengeyi, prim–fayda iliřkisini, sigortalı istihdam zerinden elde edilen prim gelirlerini ve kurumsal uyum olanaklarını ele almaktadır. Bunlar ampirik olarak sınanmıř hipotezler deėil, literatrn deėerlendirilmesine yn veren analitik beklentilerdir.

Arařtırmada btnleřtirici literatr taraması ile tematik sentezi bir araya getiren nitel bir tasarım kullanılmıřtır. Literatr Scopus, Web of Science, Google Scholar, JSTOR ve SSRN zerinden belirlenmiř; yapay zekâ, otomasyon ve teknolojik iřsizlik kavramları, istihdam, iřgc ikamesi, sosyal koruma, sosyal gvenlik finansmanı ve robot vergilendirmesiyle birlikte taranmıřtır. Aėırlık 2010–2026 dnemindeki yayınlara verilmiř, kuramsal ve kurumsal temeller bakımından gerekli nceki alıřmalar da kapsama alınmıřtır. İncelenen 58 kaynaktan arařtırma sorularıyla iliřkisi ve kavramsal senteze katkısı doėrultusunda 46’sı nihai analize dâhil edilmiřtir. Kaynak seėimi kapsamlı bir sistematik tarama iddiasına deėil, analitik uygunluėa dayanmaktadır. Literatr; teknolojik iřsizlik ve iřgc ikamesi, iřgc piyasalarının dnřm ve beceri kutuplařması, prim esaslı finansmana etkiler ve alternatif finansman modellerini de ieren politika uyum mekanizmaları olmak zere drt tema altında deėerlendirilmiřtir.

Literatür, otomasyonun istihdam sonuçlarının sektörlere, firmalara, görevlere ve kurumsal koşullara göre farklılaştığını göstermektedir. Bazı araştırmalar istihdam ve ücret kayıpları ortaya koyarken, diğerleri verimlilik ve üretim artışlarının emek talebini destekleyebildiğine işaret etmektedir. Bu nedenle otomasyona maruz kalma düzeyi, doğrudan gelecekteki iş kaybı olarak yorumlanmamalıdır. Sosyal güvenlik açısından belirleyici olan, bu karşıt etkilerin sigortalı istihdam ve prime esas kazançlar üzerindeki net sonucudur. İşgücü ikamesinin güçlü ve kalıcı olduğu durumlarda prim tabanı daralabilir. Platform çalışması ve standart dışı istihdam biçimleri de kapsam ve prim tahsilatı bakımından güçlükler yaratabilir. Buna karşılık dijital teknolojiler, sosyal güvenlik kurumlarının hizmet sunumunu ve idari kapasitesini geliştirebilir.

Çalışmada önerilen Teknolojik İşsizlik Primi, otomasyonun bu finansman sonuçlarına yönelik kavramsal bir mekanizmadır. Öneride yükümlülük, bir firmanın robot veya yapay zekâ kullanmasına doğrudan bağlanmamaktadır. Esas alınan durum, otomasyona atfedilebilen, ölçülebilir ve kalıcı sigortalı istihdam ya da prime esas kazanç kaybıdır. Bu yönüyle mekanizma, robotik sermayeyi, teknolojinin ürettiği ekonomik değeri veya yapay zekâ gelirlerini esas alan finansman yaklaşımlarından ayrılmaktadır. Prim, mevcut sosyal güvenlik yapısı içinde işveren tarafında doğabilecek ek bir katkı olarak tasarlanmıştır. Etkilenen çalışanlara doğrudan ilave prim yüklenmesi öngörülmemektedir. Devletin mevcut finansman ve idare rolü korunmakta, öneri kapsamında sabit bir eş finansman yükümlülüğü tanımlanmamaktadır.

Uygulama çerçevesinde yükümlülüğün belirlenmesi ile ödenecek tutarın hesaplanması ayrı aşamalar olarak ele alınmaktadır. İlk aşamada istihdam ve ücret toplamındaki değişimler, otomasyonun zamanı ve yoğunluğu, görev yapısındaki dönüşüm, verimlilik ve sektörel eğilimler birlikte değerlendirilebilir. Yükümlülük koşulları oluştuğunda tutar, belirlenen işgücü ikamesiyle ilişkili tahmini prim tabanı veya prim geliri kaybına bağlanabilir. Çalışma sayısal bir prim oranı ya da hesaplama formülü önermemektedir. Bu parametrelerin ulusal ve sektörel verilerle belirlenmesi gerekmektedir. Sosyal güvenlik kurumları, vergi idareleri, çalışma alanındaki kamu kurumları ve istatistik kuruluşları arasında veri paylaşımı ve görev dağılımı da uygulamanın önemli koşullarıdır. Elde edilecek gelirin öncelikli işlevi prim kaybını kısmen karşılamaktır; ulusal düzenlemelere bağlı olarak işsizlik koruması ve yeniden beceri kazandırma faaliyetleri de desteklenebilir.

Mekanizmanın en güç yanı, gözlenen istihdam kaybını otomasyona atfetmektir. Talep değişimleri, dış kaynak kullanımı, ekonomik dalgalanmalar veya işletmenin yeniden yapılanması benzer sonuçlar doğurabilir. Bu nedenle yalnızca yatırım öncesi ve sonrası istihdamı karşılaştırmak yeterli değildir; güvenilir karşılaştırmalar ve karşıolgusal değerlendirmeler gerekir. Sektörel farklılıklar, veri

eksiklikleri, idari kapasite ve firmaların yükümlülükten kaçınmaya yönelik davranışları da uygulanabilirliği etkileyebilir. Teknolojik tarafsızlık, yatırım kararlarının hiç etkilenmeyeceği varsayımı değil, tasarıma yön veren bir amaçtır. Primin istihdam, yatırım ve verimlilik üzerindeki olası etkileri ayrıca incelenmelidir.

Sonuç olarak çalışma, otomasyonun sosyal güvenlik finansmanına etkisini kaçınılmaz bir gelir kaybı olarak görmemekte; riski sigortalı istihdam ve prime esas kazançlardaki kalıcı aşınma koşuluyla ilişkilendirmektedir. Teknolojik İşsizlik Primi, mevcut işgücü ve sosyal koruma politikalarının yerini alacak kesin bir çözüm olarak sunulmamaktadır. Önerinin uygulanabilirliği, mali getirisi ve davranışsal sonuçları henüz ampirik olarak doğrulanmamıştır. Firma ve sektör düzeyindeki araştırmalar, benzetim modelleri ve pilot uygulamalar, mekanizmanın hangi koşullarda yararlı olabileceğini değerlendirmek için gereklidir.

Beyanlar

Çıkar Çatışması Beyanı

Yazar, bu makalenin yayımlanmasına ilişkin herhangi bir çıkar çatışması bulunmadığını beyan eder. Yazar, araştırmanın, potansiyel bir çıkar çatışması olarak değerlendirilebilecek herhangi bir ticari veya finansal ilişki olmaksızın yürütüldüğünü teyit eder.

Destek ve Teşekkür Beyanı

Yazar, bu çalışma için herhangi bir finansal, kurumsal veya diğer dış destek almamıştır. Teşekkür beyanı bulunmamaktadır.

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. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- 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>
- Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial intelligence: The ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives*, 33(2), 31–50. <https://doi.org/10.1257/jep.33.2.31>
- Alper, Y. (2018). Temel sosyal politika sorunları: Sosyal güvenlik. In A. Tokol & Y. Alper (Eds.), *Sosyal politika*. Dora Basım Yayın.
- Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (OECD Social, Employment and Migration Working Papers No. 189). OECD Publishing. <https://doi.org/10.1787/5jlz9h56dvq7-en>
- Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of the U.S. labor market. *American Economic Review*, 96(2), 189–194. <https://doi.org/10.1257/000282806777212620>
- Behrendt, C., Nguyen, Q. A., & Rani, U. (2019). Social protection systems and the future of work: Ensuring social security for digital platform workers. *International Social Security Review*, 72(3), 17–41. <https://doi.org/10.1111/issr.12212>
- Boulanin, V. (2019). Artificial intelligence: A primer. In V. Boulanin (Ed.), *The impact of artificial intelligence on strategic stability and nuclear risk: Volume I. Euro-Atlantic perspectives* (pp. 13–25). Stockholm: Stockholm International Peace Research Institute. <https://www.sipri.org/sites/default/files/2019-05/sipri1905-ai-strategic-stability-nuclear-risk.pdf>
- Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889–942. <https://doi.org/10.1093/qje/qjae044>
- Cabeçais de Carvalho, M. A. (2026). IoT, artificial intelligence, cloud computing and robotics and the contributory principle on social security. *AI and Ethics*, 6, Article 213. <https://doi.org/10.1007/s43681-026-01045-y>
- Calligaro, F., & Cetrángolo, O. (2023). *Financing universal social protection: The relevance and labour market impacts of social security contributions* (WIEGO Working Paper No. 47). WIEGO and International Labour Organization. <https://www.wiego.org/wp-content/uploads/2023/06/wiego-working-paper-no47.pdf>

- Casas, P., & Torres, J. L. (2026). Automation, taxation, and social security sustainability. *Hacienda Pública Española/Review of Public Economics*, 256(1), 69–104. <https://doi.org/10.7866/HPE-RPE.26.1.3>
- Costinot, A., & Werning, I. (2023). Robots, trade, and luddism: A sufficient statistic approach to optimal technology regulation. *The Review of Economic Studies*, 90(5), 2261–2291. <https://doi.org/10.1093/restud/rdac076>
- Díaz, A., & Grau Ruiz, M. A. (2020). Social security and robotization: Possible ways to finance human reskilling and promote employment. *Paladyn, Journal of Behavioral Robotics*, 11(1), 340–350. <https://doi.org/10.1515/pjbr-2020-0020>
- Dilik, S. (1992). *Sosyal güvenlik*. Ankara Üniversitesi Basımevi.
- 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>
- 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>
- Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509–2526. <https://doi.org/10.1257/aer.104.8.2509>
- Goudswaard, K., & Caminada, K. (2015). Social security contributions: Economic and public finance considerations. *International Social Security Review*, 68(4), 25–45. <https://doi.org/10.1111/issr.12086>
- Guerreiro, J., Rebelo, S., & Teles, P. (2022). Should robots be taxed? *The Review of Economic Studies*, 89(1), 279–311. <https://doi.org/10.1093/restud/rdab019>
- Holtmann, S., Braun, A.-S., Cho, J., Koch, R., & Langenmayr, D. (2025). *Investment effects of a quasi-robot tax: Evidence from South Korea* (WU International Taxation Research Paper Series No. 2025-14). WU Vienna University of Economics and Business. <https://doi.org/10.2139/ssrn.5932438>
- Hötte, K., Theodorakopoulos, A., & Koutroumpis, P. (2024). Automation and taxation. *Oxford Economic Papers*, 76(4), 945–969. <https://doi.org/10.1093/oeq/gpae006>
- Immervoll, H. (2024). *Financing social protection in OECD countries: Role and uses of revenue earmarking* (OECD Social, Employment and Migration Working Papers No. 312). OECD Publishing. <https://doi.org/10.1787/0d53155c-en>
- International Labour Organization. (2002). *Social security data required for the valuation of a national social security system*. International Labour Office.
- International Labour Organization. (2024). *World Social Protection Report 2024–26: Universal social protection for climate action and a just transition*. International Labour Office. <https://doi.org/10.54394/ZMDK5543>

- International Social Security Association. (2025, June 10). *Global overview of social security reforms 2023–2025*. <https://www.issa.int/analysis/global-overview-social-security-reforms-2023-2025>
- Kang, D., Lee, J. H., & Quach, S. (2024). *The welfare effects of a robot tax: Evidence from a tax credit for automation technologies in Korea*. SSRN. <https://doi.org/10.2139/ssrn.5005128>
- Korkusuz, R., & Uğur, S. (2010). *Sosyal güvenlik hukukuna giriş*. Karahan Kitabevi.
- Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, 6(4), 239–242. <https://doi.org/10.1007/s12599-014-0334-4>
- Nilsson, N. J. (1998). *Artificial intelligence: A new synthesis*. Morgan Kaufmann.
- OECD. (2024a). *Megatrends and the future of social protection*. OECD Publishing. <https://doi.org/10.1787/6c9202e8-en>
- OECD. (2024b). *Revenue statistics 2024*. OECD Publishing. <https://doi.org/10.1787/c87a3da5-en>
- Peetz, D. (2019). Digitalisation and the jobs of the future. In *The realities and futures of work* (pp. 145–166). ANU Press. <https://www.jstor.org/stable/j.ctvq4c16w.9>
- 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>
- Şakar, M. (2017). *Sosyal sigortalar uygulaması*. Beta Yayınları.
- Talas, C. (1983). *Sosyal ekonomi*. Ankara Üniversitesi SBF Yayını.
- Thuemmel, U. (2023). Optimal taxation of robots. *Journal of the European Economic Association*, 21(3), 1154–1190. <https://doi.org/10.1093/jeaa/jvac062>
- Tuncay, A. C., & Ekmekçi, Ö. (2015). *Sosyal güvenlik hukuku dersleri* (Yenilenmiş 17. bastı). Beta.
- Turner, M. (2026). *The bot tax: Why AI systems should pay social security on the wages they replace—A labor displacement levy proposal with empirical case study*. SSRN. <https://doi.org/10.2139/ssrn.6723920>
- Tyson, L. D., & Zysman, J. (2022). Automation, AI & work. *Daedalus*, 151(2), 256–271. https://doi.org/10.1162/daed_a_01914
- UNU-EGOV. (2023). *Digital transformation of social security administration and services: A comparative analysis of Australia, Canada, Denmark and France* (ILO Working Paper No. 93). Geneva: International Labour Office. <https://doi.org/10.54394/RRID1984>
- Virgilio, G. P. M., Saavedra Hoyos, F., & Bao Ratzemberg, C. B. (2024). The impact of artificial intelligence on unemployment: A review. *International Journal of Social Economics*, 51(12), 1680–1695. <https://doi.org/10.1108/IJSE-05-2023-0338>

- Wang, L., Liu, C., Liu, D., & Zhang, Y. (2025). Beyond jobs and wages: The hidden cost of automation on corporate social security contributions. *International Review of Financial Analysis*, 106, 104516. <https://doi.org/10.1016/j.irfa.2025.104516>
- Whittemore, R., & Knafl, K. (2005). The integrative review: Updated methodology. *Journal of Advanced Nursing*, 52(5), 546–553. <https://doi.org/10.1111/j.1365-2648.2005.03621.x>
- Zhang, L., Gan, T., & Fan, J. (2023). Do industrial robots affect the labour market? Evidence from China. *Economics of Transition and Institutional Change*, 31(3), 787–817. <https://doi.org/10.1111/ecot.12356>

