Discussion Paper Series

IZA DP No. 19026

October 2026

Beyond Exposure: AI and Labor Market Reorganization in Türkiye

Mpumelelo Nxumalo
World Bank

Dhushyanth Raju
World Bank and IZA@LISER

The IZA Discussion Paper Series (ISSN: 2365-9793) ("Series") is the primary platform for disseminating research produced within the framework of the IZA@LISER Network, an unincorporated international network of labour economists coordinated by the Luxembourg Institute of Socio-Economic Research (LISER). The Series is operated by LISER, a Luxembourg public establishment (établissement public) registered with the Luxembourg Business Registers under number J57, with its registered office at 11, Porte des Sciences, 4366 Esch-sur-Alzette, Grand Duchy of Luxembourg.

Any opinions expressed in this Series are solely those of the author(s). LISER accepts no responsibility or liability for the content of the contributions published herein. LISER adheres to the European Code of Conduct for Research Integrity. Contributions published in this Series present preliminary work intended to foster academic debate. They may be revised, are not definitive, and should be cited accordingly. Copyright remains with the author(s) unless otherwise indicated.

IZA DP No. 19026 October 2026

Beyond Exposure: AI and Labor Market Reorganization in Türkiye*

Abstract

Occupational exposure to artificial intelligence (AI) identifies where technology may affect work, but not how employment will adjust. Using microdata from Türkiye's 2024 Household Labor Force Survey, this paper applies the Richmond (2026a) AI Jobs Transition Framework to a sample representing 27.7 million private sector workers. The framework combines AI exposure with demand responsiveness (whether productivity gains generate enough additional demand to offset lower labor requirements per unit of output) and human necessity (whether production or service delivery continues to require human participation). These dimensions distinguish four potential adjustment mechanisms: Automation Risk, Reorganize, Grow with AI, and Less Change. Reorganize accounts for the largest share of high-exposure employment, representing 21.3 percent of private sector employment, compared with 12.3 percent in Automation Risk and 7.7 percent in Grow with AI; 58.7 percent falls into Less Change. Reorganize occupations combine high exposure, constrained demand, and high human necessity, indicating greater potential for adjustment through weaker hiring, lower labor intensity, or changes in work organization than through more direct labor-saving substitution. The results show that occupational exposure alone masks important differences in how AI may affect employment and that demand conditions and continuing human involvement help distinguish these adjustment mechanisms.

JEL classification

J23, J24, J46, O33, O15

Keywords

artificial intelligence, occupational exposure, labor market adjustment, employment reorganization, informality, technological change, Türkiye

Corresponding author

Dhushyanth Raju
draju2@worldbank.org

* We thank Alex Martin Richmond and Iván Torre for helpful comments.

1. Introduction

Artificial intelligence (AI) is increasingly able to perform and assist with cognitive tasks and to reorganize how those tasks are carried out, renewing debate over how technological change will affect employment (Acemoglu and Restrepo 2019a, 2019b; Autor 2022; Autor, Levy, and Murnane 2003; Eloundou et al. 2024). Yet occupational exposure to AI does not determine how employment will adjust. The same technology may substitute for labor in some tasks, complement workers in others, and expand demand where productivity gains lower costs, improve quality, or extend market reach (Acemoglu and Restrepo 2019b; Bessen 2019; Brynjolfsson, Li, and Raymond 2025; Noy and Zhang 2023). The key question is not only where AI can affect work, but how employment is likely to adjust when AI is adopted.

A growing literature measures occupational AI exposure by mapping advances in machine learning and generative AI to workplace tasks (Eloundou et al. 2024; Felten, Raj, and Seamans 2021; Gmyrek et al. 2025; Webb 2020). Subsequent work incorporates complementarity, recognizing that exposure need not imply substitution and that AI may augment workers even where it substantially changes task content (Cazzaniga et al. 2025; Pizzinelli et al. 2023). A related strand examines actual AI adoption and use. Using nationally representative U.S. surveys, Bick, Blandin, and Deming (2026) document rapid workplace adoption of generative AI. Massenkoff and McCrory (2026), in turn, combine measures of technological capability with real-world usage data to distinguish potential exposure from observed exposure.

Emerging evidence on labor market responses provides a further step beyond exposure and use. Studies using vacancies and online job postings document early changes in hiring demand and skill requirements across occupations and establishments with different levels and types of AI exposure (Acemoglu et al. 2022; Chen, Srinivasan, and Zakerinia 2025). Related evidence shows relative declines in postings for occupations with greater AI-substitution vulnerability following ChatGPT's release (Liu, Wang, and Yu 2025). Recent evidence further suggests that adjustment may occur through hiring and workforce composition before becoming visible in aggregate employment. U.S. payroll data show weaker employment among young workers in highly exposed occupations, driven mainly by reduced hiring (Brynjolfsson, Chandar, and Chen 2026). Cross-country adoption evidence, in turn, points to a shift in workforce composition from junior toward senior employment within adopting firms (Chandar and Klein Teeselink 2026). These strands distinguish technological capability from actual use and document early labor demand responses, but they do not explain why similarly exposed occupations may follow different adjustment mechanisms.

Richmond (2026a) addresses this gap through the AI Jobs Transition Framework, developed and applied to the United States. The framework combines AI exposure with demand elasticity and human necessity. Exposure identifies occupations in which AI can perform or assist with important tasks. Demand elasticity captures whether productivity-related reductions in effective cost generate enough additional demand to offset lower labor requirements per unit of output. Human necessity captures whether producing or delivering the relevant good or service continues to require human participation. These dimensions distinguish four archetypes: Automation Risk, Reorganize, Grow with AI, and Less Change. The framework shifts the analysis from technological exposure to potential labor market adjustment mechanisms.

The framework is particularly relevant for middle-income economies characterized by dual labor markets. In many such economies, widespread informality, a large share of employment in small firms, and lower purchasing power may shape how AI-driven productivity gains translate into employment. In particular, limited demand expansion can weaken the scale effect that offsets labor-saving productivity gains (Bessen 2019). Under these conditions, adjustment may be more likely to occur through weaker hiring, consolidated task bundles, lower labor requirements per unit of output, or changes in employment arrangements within continuing occupations than through rapid occupational disappearance. These margins may be less visible than layoffs but remain important for labor market policy.

Türkiye provides a useful setting for examining these mechanisms because its private sector combines exposed formal service and professional employment with substantial lower-exposure employment in agriculture, construction, transport, manual occupations, and informal work. This combination permits comparison of exposed cognitive and service occupations with lower-exposure physical occupations within a single labor market and reveals how archetype distributions vary across sectors, regions, and formal and informal employment. The paper asks how high-exposure employment in Türkiye is distributed across alternative adjustment mechanisms and, in particular, whether it is concentrated primarily in Automation Risk or Reorganize.

This paper applies the Richmond framework to Türkiye's 2024 Household Labor Force Survey (HLFS) microdata from the Turkish Statistical Institute (TurkStat). The analytical sample covers private sector workers across International Standard Classification of Occupations, 2008 revision (ISCO-08) two-digit occupations and represents 27.7 million workers after applying survey weights. The analysis combines the complementarity-adjusted AI occupational exposure measure developed by Pizzinelli et al. (2023) and applied to Türkiye by Aşık et al. (2026) with constructed demand elasticity inputs tailored to Turkish market conditions. Human necessity scores are derived from the Occupational Information Network (O*NET) measures of physical execution and live care and teaching and mapped to ISCO-08. Occupation-level demand elasticities are not directly observed, so the paper constructs them through a structured, profile-based elicitation procedure using Claude Sonnet 4.6.

Reorganize is the largest high-exposure archetype, accounting for 21.3 percent of private sector employment, compared with 12.3 percent in Automation Risk and 7.7 percent in Grow with AI; 58.7 percent falls into Less Change. Reorganize occupations combine high exposure, relatively low constructed demand responsiveness, and high human necessity, indicating greater potential for adjustment through weaker hiring, lower labor intensity, or changes in work organization than through more direct labor-saving substitution.

Sales workers are the largest occupation group in Reorganize, accounting for 10.6 percent of private sector employment. Their classification reflects high exposure and human necessity combined with a sector-weighted demand elasticity input that incorporates the retail-heavy composition of sales employment. Their large employment share makes this classification consequential for the aggregate Reorganize share.

The archetypes also vary systematically across workers and economic settings. Women, tertiary-educated workers, and formal workers are more concentrated in high-exposure occupations, although their distribution across Automation Risk, Reorganize, and Grow with AI differs. Informal workers are concentrated mainly in Less Change occupations. Sectoral differences are also pronounced: trade is dominated by Reorganize, manufacturing combines substantial Reorganize and Grow with AI shares, and agriculture, construction, transport, and other physical activities remain largely in Less Change.

The paper makes three contributions. First, it moves beyond occupational exposure by distinguishing alternative mechanisms of employment adjustment within high-exposure occupations. Second, it shows how demand responsiveness and continuing human necessity can separate potential labor-saving substitution from reorganization and demand-driven expansion. Third, it demonstrates how the framework can be operationalized using ISCO-based labor force survey data in a middle-income economy without detailed national occupational task data.

The findings imply differentiated policy priorities across the four archetypes: transition support and early monitoring for Automation Risk occupations, in-work adaptation for Reorganize occupations, measures that ease constraints on demand expansion for Grow with AI occupations, and preparedness for future technological reach in Less Change occupations. Labor market institutions also need to detect gradual adjustment early and support workers before displacement becomes visible.

The analysis is diagnostic rather than predictive. It uses complementarity-adjusted AI occupational exposure and constructed demand elasticity and human necessity inputs to distinguish potential mechanisms of employment adjustment. It does not measure actual AI adoption, estimate causal employment effects, or forecast job losses. Its contribution is to identify how employment in exposed occupations may adjust, rather than predict the magnitude or timing of those adjustments.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature and presents the conceptual framework. Section 3 describes the data and measurement approach. Sections 4 and 5 report the aggregate and disaggregated results. Section 6 places the findings in comparative perspective. Section 7 discusses policy implications, and Section 8 concludes.

2. Related Literature and Conceptual Framework

AI Exposure, Complementarity, and Employment Effects

Research on technological change has long emphasized that technologies affect workers through tasks rather than occupations as indivisible units (Acemoglu and Restrepo 2019b; Autor, Levy, and Murnane 2003). Recent advances in AI have made this task-based perspective increasingly important as large language models and related systems can perform or assist with a widening range of cognitive tasks. A growing literature measures occupational AI exposure by mapping technological capabilities to workplace tasks. Much of the early measurement literature was developed using U.S. occupational data and finds greater exposure in occupations involving information processing, clerical work, communication, coding, and analysis (Eloundou et al. 2024; Felten, Raj, and Seamans 2021; Webb 2020). Recent global analyses document similar patterns

across countries and highlight variation associated with occupational structure and income level (Cazzaniga et al. 2024; Gmyrek et al. 2025).

Subsequent work incorporates complementarity, recognizing that exposure need not imply labor substitution. AI may augment workers by increasing the speed, quality, or scope of task performance even where it substantially changes occupational content. In other cases, it may substitute more directly for routine cognitive activities. Pizzinelli et al. (2023) incorporate complementarity into a measure of occupational AI exposure and apply it across countries. Using measures of occupational AI exposure and task complementarity, Aşık et al. (2026) show that high-exposure employment in Türkiye spans occupations with differing potential for labor substitution and augmentation.

A related strand examines actual AI adoption and use rather than technological capability alone. Using nationally representative U.S. surveys, Bick, Blandin, and Deming (2026) document rapid diffusion of generative AI at work and substantial variation in its prevalence and intensity across workers and industries. Massenkoff and McCrory (2026) combine task-level measures of AI capability with anonymized usage data to construct an observed exposure measure that weights occupations by actual work-related AI use in the United States. These approaches narrow the gap between what AI can do and how it is being used, but they do not by themselves determine whether exposed occupations will contract, reorganize, or expand.

Experimental and firm-level studies show that generative AI can raise productivity and improve quality in selected cognitive tasks (Brynjolfsson, Li, and Raymond 2025; Dell'Acqua et al. 2026; Noy and Zhang 2023). These studies examine particular tasks, firms, or work settings rather than national employment effects and do not establish whether firms will expand output and employment, reorganize work, or reduce labor demand.

Emerging labor market evidence provides an important but still incomplete picture and remains concentrated in advanced economies. Studies using U.S. vacancies and online job postings document changes in vacancies, occupational hiring demand, and requested skills across occupations and establishments with different levels and types of AI exposure (Acemoglu et al. 2022; Chen, Srinivasan, and Zakerinia 2025). Related evidence shows declines in postings for occupations with greater AI-substitution vulnerability following ChatGPT's release (Liu, Wang, and Yu 2025). Massenkoff and McCrory (2026) find no systematic evidence to date of higher unemployment in U.S. occupations with greater observed exposure, but they report suggestive evidence of weaker hiring among younger workers. Evidence from Denmark similarly documents rapid workplace adoption, reported productivity gains, and the emergence of new AI-related tasks, with limited early changes in earnings and recorded hours (Humlum and Vestergaard 2025).

More recent evidence points to hiring and workforce composition as important early margins of adjustment. U.S. payroll data show a widening employment shortfall among young workers in highly exposed occupations, driven primarily by reduced hiring rather than increased separations (Brynjolfsson, Chandar, and Chen 2026). Cross-country evidence from AI-adopting firms similarly shows a shift in workforce composition away from junior workers, driven primarily by growth in senior employment (Chandar and Klein Teeselink 2026). These studies suggest that

adjustment may emerge through hiring, requested skills, task organization, workforce composition, and workplace practices before becoming visible in aggregate employment stocks.

Exposure and complementarity describe occupational susceptibility. Adoption measures capture whether AI is used, and observed exposure measures link work-related use to occupational tasks. None of these dimensions alone determines employment outcomes. Employment effects also depend on whether productivity gains expand demand (Acemoglu 2024; Bessen 2019) and, in the Richmond framework, whether workers remain integral to producing or delivering the relevant good or service (Richmond 2026a). This implies that occupations with similar exposure may experience different forms of adjustment depending on complementarity, actual use, demand conditions, and the continuing role of human labor.

This evidence still does not fully identify the mechanisms through which employment may adjust. Much of the early labor market evidence also comes from the United States and other advanced economies. Recent cross-country evidence extends to middle-income economies but is concentrated in digitally connected multinational firms, leaving the implications for broader dual labor markets uncertain (Chandar and Klein Teeselink 2026). Moving from technological exposure, observed use, task-level productivity, and early labor demand responses to employment contraction, reorganization, or growth requires additional information about demand responsiveness and the continuing role of human labor.

The Richmond Framework: From Exposure to Adjustment Mechanisms

Richmond (2026a) addresses this gap by combining three dimensions: AI exposure, demand elasticity, and human necessity. AI exposure identifies occupations in which AI can perform or assist with important tasks. Demand elasticity captures whether AI-induced reductions in the effective cost of producing or delivering the relevant good or service generate enough additional demand to offset lower labor requirements per unit of output. Human necessity captures whether producing or delivering the relevant good or service continues to require human participation even when AI can perform or assist with important component tasks.

Demand elasticity represents the scale effect of AI-driven productivity gains. In this framework, it refers to the responsiveness of demand to a reduction in the effective cost of producing or delivering the relevant good or service, not to the wage elasticity of labor demand. When AI raises productivity and lowers effective costs, employment is more likely to be sustained if the resulting expansion in output offsets the decline in labor required per unit. Where demand is relatively elastic, greater output or service use may sustain or increase employment. Where demand is less responsive, productivity may rise faster than output, weakening hiring, employment growth, or labor intensity. This demand channel is related to the scale effect in task-based models of AI adoption, although firm-level expansion need not translate one-for-one into aggregate employment growth because aggregate outcomes also depend on reallocation and general equilibrium responses (Acemoglu 2024; Acemoglu and Restrepo 2019b).

Human necessity captures a separate mechanism. Occupations may continue to require human participation when physical presence, interpersonal interaction, care work, teaching, accountability, professional judgment, trust, or real-time response remains integral to delivery. AI

may substantially assist workers in such occupations without eliminating the economic need for human involvement.

Complementarity and human necessity are related but distinct. Complementarity concerns whether AI raises the productivity of workers performing particular tasks. Human necessity concerns whether delivery of the final good or service continues to require human participation even when those tasks can be technologically assisted. An occupation may be highly complementary with AI but have low human necessity if the service can ultimately be delivered with little human involvement. Conversely, an occupation may have modest complementarity but high human necessity if human participation remains integral to delivery.

Combining the three dimensions produces four archetypes. Occupations below the framework's AI-exposure threshold are classified as Less Change. Among occupations above that threshold, those meeting the demand elasticity criterion are classified as Grow with AI. High-exposure occupations that do not meet that criterion are classified as Automation Risk when human necessity is low and Reorganize when human necessity is high.

A defining feature of the framework is that it separates Automation Risk from Reorganize. Automation Risk identifies high-exposure occupations in which relatively low demand responsiveness and low human necessity create greater potential for labor-saving adjustment. Reorganize identifies high-exposure occupations in which relatively low demand responsiveness is combined with high human necessity, indicating greater potential for adjustment through changes in task composition, work organization, hiring, or labor intensity than through elimination of the occupation. Reorganize is not an intermediate category between automation and growth. It represents a distinct potential adjustment mechanism in which the occupation continues to require human participation even though the amount or composition of labor required may change.

The framework shifts attention from automation as a binary outcome to a broader set of adjustment margins, including direct substitution, slower recruitment, weaker employment growth, changing task content, and work reorganization.

The framework abstracts from the timing of AI adoption, wage adjustment, firm-level technology choices, sectoral reallocation, and economy-wide feedback effects. Its archetypes represent alternative adjustment mechanisms rather than predetermined employment outcomes. Occupations assigned to the same archetype may experience different outcomes across firms, sectors, and institutional settings, depending on how technology is adopted and how production and labor demand respond.

Why Middle-Income and Dual Labor Markets May Differ

The relationship between AI-driven productivity and employment may differ across countries because demand conditions, firm structure, occupational composition, and labor market institutions vary. In many middle-income economies, lower household purchasing power, a large share of employment in small firms, and occupational concentration in activities where demand expansion may be limited may weaken the scale effects associated with AI-driven cost reductions (Bessen 2019). These features may be especially relevant in retail, personal services, food services,

and other activities in which lower costs do not necessarily generate proportionate increases in consumption or market size.

Under these conditions, adjustment may be more likely to occur within continuing occupations than through immediate occupational disappearance. Productivity gains may allow firms to maintain or expand output with slower hiring, lower labor requirements per unit of output, consolidated task bundles, or different employment arrangements. These margins are less visible than layoffs but may be especially important where formal job creation is already constrained.

Informality adds an institutional dimension. In many middle-income labor markets, informal employment is concentrated in physical, manual, and real-time occupations that current generative AI systems affect less directly. However, lower current exposure does not necessarily imply greater resilience. Exposure captures the extent to which current AI capabilities can affect occupational tasks, whereas resilience also depends on workers' capacity to adapt. Informal workers often have weaker access to employer-provided training, public employment services, social insurance, and other forms of transition support. If AI capabilities expand further into physical and embodied tasks, workers who are less exposed today may have less capacity to adjust.

The formal-informal divide may also shape how adjustment appears. In exposed formal occupations, potential adjustment may first emerge through reduced entry-level recruitment or changes in workforce composition (Brynjolfsson, Chandar, and Chen 2026; Chandar and Klein Teeselink 2026), as well as through changing skill requirements and task organization (Acemoglu et al. 2022; Humlum and Vestergaard 2025). Where formal and informal work coexist, restructuring could also shift some workers toward less protected employment arrangements, although this paper does not test that possibility.

Türkiye combines these features within a single labor market, characterized by a sizable formal service and production economy and substantial employment in agriculture, construction, transport, manual occupations, and informal work. This composition provides a useful setting in which to assess whether high-exposure employment is concentrated primarily in Automation Risk or Reorganize and how the archetype distribution differs between formal and informal employment.

3. Data and Measurement Framework

Data and Analytical Sample

The analysis uses microdata from Türkiye's 2024 HLFS. The survey is nationally representative and provides information on employment status, occupation, sector, region, educational attainment, age, gender, establishment size, and social security registration. Unless otherwise noted, worker counts and employment shares are calculated using the official final person-level HLFS survey weight, without normalization, rescaling, or recalibration.

The analytical sample is restricted to private sector workers because the framework focuses on employment adjustment through market demand, productivity, and firms' labor use decisions. These mechanisms may operate differently in the public sector, where employment is shaped more

directly by administrative rules, budgetary processes, and institutional protections. The resulting sample contains 180,908 unweighted observations and represents approximately 27.7 million private sector workers.

Occupations are classified at the two-digit level of the ISCO-08. The analysis covers 39 occupation groups, the most detailed level at which the available HLFS occupation codes can be linked consistently to the framework's three inputs: AI exposure, demand elasticity, and human necessity. This level preserves meaningful variation across occupation groups but abstracts from heterogeneity within them.

Sector of employment is classified using the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2). Sector information is used both to report disaggregated results and, for sales workers, to construct a sector-weighted elasticity for a large and heterogeneous occupation whose demand conditions vary across employing sectors. Employment formality is defined by social security registration in the worker's main job. Including both formal and informal workers allows the archetype distribution to be examined across Türkiye's dual labor market.

Each worker is assigned the archetype of their ISCO-08 two-digit occupation, so all workers within an occupation group receive the same classification. Aggregate and subgroup shares are then calculated using HLFS survey weights. The resulting estimates describe the weighted distribution of private sector employment across occupation-level archetypes; they do not measure actual AI use by workers or firms.

Measuring AI Exposure

Occupational AI exposure is measured using the C-AIOE measure developed by Pizzinelli et al. (2023). The measure builds on task-based AI exposure by adjusting raw exposure for the extent to which AI is expected to complement, rather than substitute for, human labor.

The C-AIOE values used in this paper draw on the occupational AI exposure and complementarity measures applied to HLFS microdata and matched employer–employee administrative records from Türkiye's Enterprise Information System (EIS) by Aşık et al. (2026), but use a different mapping to ISCO-08 two-digit occupations. Each two-digit occupation group is assigned the C-AIOE value associated with the corresponding four-digit aggregate code ending in "00," rather than an average across constituent four-digit occupations.

C-AIOE measures occupational task exposure, not actual AI adoption.

The high-exposure threshold is the employment-weighted mean C-AIOE value across the 39 occupation groups, equal to 4.437. Employment weighting makes the threshold reflect the average exposure faced by private sector workers rather than giving equal weight to occupations of very different employment sizes. Occupations with $C\text{-}AIOE \geq 4.437$ proceed to the demand elasticity stage of the classification; those with $C\text{-}AIOE < 4.437$ are classified as Less Change.

Using complementarity-adjusted exposure as the first-stage filter differs from beginning with a purely technical exposure measure and incorporating complementarity only at a later stage. As a result, some occupations with substantial technical exposure may fall below the high-exposure threshold before reaching the demand elasticity and human necessity stages. This choice follows the Türkiye-specific C-AIOE mapping of Aşık et al. (2026), but it reduces direct comparability with Richmond's original implementation and may be particularly consequential for occupations such as teaching and health, where substantial technical exposure can coexist with strong complementarity.

Measuring Demand Elasticity

Demand elasticity captures whether productivity-related reductions in the effective cost of producing or delivering the relevant good or service generate enough additional demand to offset lower labor requirements per unit of output. It is defined as the percentage change in quantity demanded associated with a 1 percent change in effective cost and is distinct from the wage elasticity of labor demand.

The relevant demand object varies by occupation. It may be a final good or service purchased by consumers, an intermediate input used by firms, a professional or technical service, or an internal organizational function arising from production and management needs.

Direct estimates of these elasticities are generally unavailable at the occupation level, particularly in middle-income economies. The paper constructs demand elasticity inputs through a structured elicitation procedure using Claude Sonnet 4.6. For each occupation, a standardized profile was prepared containing the official International Labour Organization title and definition, five representative tasks adapted to the Turkish private sector context, and a description of the associated output or service in the Turkish market. The elicitation prompt also specified relevant features of Türkiye's market structure, including its middle-income setting, small and medium-sized enterprises structure, informality, and agricultural employment. Constructing demand responsiveness for the national context rather than transferring U.S. values is consistent with the EU application of the framework, which adapts demand responsiveness to European occupational descriptions and market and institutional conditions (Richmond 2026b).

Each directly elicited occupation group was evaluated in three independent Application Programming Interface (API) calls using the same profile and prompt. The arithmetic mean across the three runs was retained as the elasticity input. Appendix A reports the exact profiles and prompt, model settings, access period, run-level values, output validation rules, rerun history, and stability diagnostics.

Sales workers were treated separately because the occupation group is large and spans sectors with materially different demand conditions. A single occupation-level profile is poorly suited to representing the relevant demand response for the group as a whole. A sector-weighted elasticity was constructed using the HLFS distribution of sales employment across employing sectors. Each sector-specific elasticity was based on three independent API calls using the same protocol applied to the other occupation groups. The resulting employment-weighted estimate is $\eta = -0.850$, placing sales workers on the constrained-demand side of the classification threshold. Sales workers

are the only occupation group receiving sector-disaggregated treatment. Appendix A reports the rationale, sector definitions, sector-specific profiles, run-level estimates, employment weights, aggregation calculation, and development history of this treatment.

Elasticity values are negative under the conventional definition, with more negative values indicating a larger increase in quantity demanded when effective cost falls. The classification uses $\eta = -1.000$ as the threshold for sufficiently elastic demand. High-exposure occupations with $\eta \leq -1.000$ are assigned to Grow with AI; those with $\eta > -1.000$ proceed to the human necessity stage. The threshold is a classification rule rather than an econometrically estimated point at which employment necessarily increases. An occupation exactly at the cutoff, $\eta = -1.000$, is assigned to Grow with AI. Food processing, woodworking, garment, and other craft and related trades workers (ISCO 75), accounting for 4.0 percent of private sector employment, lie exactly at this boundary, so their assignment depends on this convention.

Measuring Human Necessity

Human necessity captures whether human participation remains integral to producing or delivering a good or service even when AI can perform or assist with some occupational tasks. It differs from complementarity. Complementarity concerns whether AI raises workers' productivity in performing tasks; human necessity concerns whether production or service delivery continues to require human involvement.

The measure is constructed from O*NET 29.0 occupational data and operationalizes two channels:

1. **Physical execution:** direct interaction with physical environments, objects, equipment, or production processes.

2. **Live care and teaching:** care provision, instruction, direct interpersonal engagement, or responsibility for others as part of service delivery.

The physical-execution and live-care-and-teaching composites are constructed as equal-weighted averages of normalized O*NET elements. The physical-execution indicator is activated when its composite score is at least 0.52, and the live-care-and-teaching indicator when its composite score is at least 0.64.

The activation thresholds were selected during development of the rule-based measure with reference to occupation-level information reported in Richmond (2026a). They were not chosen independently of prior occupational information and were not estimated from Turkish occupational data. Appendix B examines sensitivity to alternative human necessity cutoffs.

The two composites are first constructed for detailed O*NET-SOC occupation records. Where multiple detailed O*NET variants correspond to the same six-digit Standard Occupational Classification (SOC) occupation, their physical-execution and live-care-and-teaching composite scores are averaged. The activation rules are then applied at the reconciled six-digit SOC level. Occupations meeting either criterion receive $H = 0.90$; occupations meeting neither criterion receive $H = 0.15$. These are classificatory scores distinguishing strong physical or relational

necessity from its absence, not estimates of the magnitude or probability of continuing human necessity.

The six-digit SOC scores are then mapped to ISCO-08 two-digit groups using a manual crosswalk. National employment weights from the May 2021 Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics are applied once at the six-digit SOC level, and ISCO-level values are calculated as employment-weighted means of constituent SOC scores. Six-digit SOC occupations without a positive BLS employment weight are excluded from the employment-weighted mean within their ISCO group; no ISCO group is left without at least one positively weighted constituent occupation. Appendix A reports the source elements, reconciliation of detailed occupation variants, crosswalk sources and mapping rules, treatment of missing employment weights, and aggregation procedure.

Two occupation groups without matched SOC occupations receive structured tier assignments under the same two-channel framework. Street and related sales and service workers (ISCO 95) and refuse workers and other elementary workers (ISCO 96) are assigned $H = 0.90$, reflecting the centrality of physical presence, direct interaction, on-site execution, and real-time response. These groups account for 1.23 percent of private sector employment. Appendix A reports the assignments and their rationale.

The classification uses $H = 0.50$ as the threshold for high human necessity, following Richmond (2026a). Among high-exposure occupations with constrained demand, occupations with $H \geq 0.50$ are classified as Reorganize; those with $H < 0.50$ are classified as Automation Risk.

O*NET provides standardized, detailed measures of occupational activities and work context at scale. Despite these advantages, the resulting values should be interpreted as structured occupation-level inputs derived from U.S. occupational data and mapped to the Turkish occupational classification, rather than as direct observations of job content in Türkiye.

Archetype Classification

Occupations are assigned to archetypes through a sequential classification tree. Exposure is evaluated first, demand elasticity second, and human necessity only among high-exposure occupations with constrained demand.

Step	Classification condition	Archetype
1	C-AIOE <4.437	Less Change
2	C-AIOE $\geq 4.437$and $\eta \leq -1.0$	Grow with AI
3	C-AIOE ≥ 4.437, $\eta > -1.0$, and $H \geq 0.50$	Reorganize
4	C-AIOE ≥ 4.437, $\eta > -1.0$, and $H < 0.50$	Automation Risk

Occupations below the exposure threshold are assigned to Less Change regardless of their elasticity or human necessity values. Among high-exposure occupations, values at or below the demand elasticity cutoff place an occupation in Grow with AI. Human necessity separates Reorganize from Automation Risk among high-exposure occupations above the elasticity cutoff.

Each ISCO-08 occupation group receives one archetype assignment, which is applied to all workers in that group. Weighted archetype shares are calculated by summing the HLFS weights of workers assigned to each category. Table 2 reports the occupation-level inputs and archetype assignments for all 39 occupation groups.

Interpretation and Measurement Limitations

The classifications depend on occupation-level measures, constructed inputs, and discrete thresholds that may not capture heterogeneity within occupational groups. They should be interpreted as indicators of potential adjustment mechanisms rather than estimates of employment effects. In particular, an occupation classified as Automation Risk or Reorganize is not necessarily expected to experience employment losses. The following limitations concern the measurement choices underlying these assignments.

The analysis is conducted at the ISCO-08 two-digit level. This allows nationally representative labor force survey data to be linked consistently to the three classification inputs, but it masks differences in task content across workers of different seniority levels, firms, sectors, regions, technologies, and employment arrangements within the same occupation. Recent adoption-based evidence indicates substantial differences in employment adjustment by seniority within exposed occupations, a margin this occupation-level classification cannot capture (Chandar and Klein Teeselink 2026). The sector-disaggregated treatment of sales workers addresses one consequential source of heterogeneity but does not resolve within-occupation aggregation concerns more generally.

The three inputs are measured at the occupation level, and two are constructed specifically for this application. C-AIOE is assigned through an external occupational mapping; demand elasticity is elicited from standardized occupation profiles rather than estimated from observed market responses; and human necessity is derived from O*NET and mapped from the U.S. occupational classification to ISCO-08. These procedures provide a systematic basis for comparison but may not fully capture Turkish differences in task organization, informality, digitalization, regulation, or consumer and firm demand.

The elicited demand elasticity inputs depend on the supplied profiles, prompt design, model version, run structure, and Türkiye-specific contextual assumptions. The sector-disaggregated treatment of sales workers was introduced after review of the initial occupation-level result and represents a targeted modeling choice rather than a prespecified rule. Demand responsiveness is constructed at the sector level for sales workers and aggregated using their sectoral employment distribution, whereas other occupations receive occupation-level estimates. Appendix A documents the rationale, implementation, and development history of this treatment.

The human necessity measure is deterministic given the selected O*NET elements, normalization procedure, activation thresholds, tier values, reconciliation of detailed occupation variants, crosswalk, and employment weights. These choices are reproducible given the source data and coding rules, but the resulting values are not estimated from Turkish occupational data. The measure may understate human necessity where continuing human involvement derives from formal certification or licensure, managerial authority, fiduciary responsibility, informal

accountability, or relational trust rather than physical execution or live care and teaching. This limitation reflects the exclusion of the licensed-or-certified-judgment channel from the baseline construction owing to incomplete O*NET coverage. As a result, some professional or managerial occupations classified as Automation Risk under the baseline measure could instead fall into Reorganize if licensed judgment, formal accountability, or related forms of continuing human necessity were fully captured.

The framework is partial equilibrium. It does not model wages, endogenous task creation, firm entry and exit, sectoral reallocation, product market restructuring, economy-wide demand and productivity feedbacks, or policy responses that could alter occupational adjustment.

Finally, the results depend on the selected exposure, elasticity, and human necessity thresholds. Occupations close to these cutoffs may move between archetypes under alternative specifications or as AI capabilities, demand conditions, and work organization evolve. Appendix B reports sensitivity to alternative classification thresholds.

Subject to these limitations, the framework provides a transparent basis for distinguishing among alternative occupation-level adjustment mechanisms.

4. Aggregate AI Adjustment Archetypes

The main result is that Reorganize, rather than Automation Risk, is the largest high-exposure archetype in Türkiye's private sector. Reorganize accounts for 21.3 percent of private sector employment, compared with 12.3 percent in Automation Risk and 7.7 percent in Grow with AI. Less Change accounts for the remaining 58.7 percent.

Figure 1 shows how employment is allocated across the four archetypes through the sequential exposure, demand elasticity, and human necessity filters. Table 1 summarizes the aggregate distribution, and Table 2 reports the occupation-level classification for all 39 ISCO-08 two-digit groups, including employment shares, C-AIOE values, demand elasticity inputs, human necessity scores, and archetype assignments.

The aggregate profile has two main features. Among high-exposure occupations, a larger share of employment falls into Reorganize than Automation Risk, indicating greater potential for adjustment within continuing occupations than through more direct labor-saving substitution. By contrast, the large Less Change share reflects the continued weight of physical, embodied, and real-time work in agriculture, construction, transport, personal services, and manual trades.

Appendix B examines sensitivity to alternative exposure, elasticity, and human necessity cutoffs. Less Change remains the largest archetype under all illustrated specifications. The ordering of the high-exposure archetypes is less robust. Reorganize is largest under the baseline and most illustrated one-way perturbations, but Automation Risk becomes largest when the human necessity cutoff is raised to $H = 0.60$, and Grow with AI becomes largest when the elasticity cutoff is relaxed to $\eta = -0.80$. For this reason, the finding that Reorganize is the largest high-exposure archetype should be interpreted as a baseline result that is meaningful but threshold-sensitive.

Occupations Classified as Automation Risk

Automation Risk occupations combine high AI exposure, constrained demand, and low human necessity. They account for 12.3 percent of private sector employment across seven occupation groups and are concentrated mainly in clerical, administrative, and analytical functions.

The largest groups are numerical and material recording clerks, at 3.5 percent of private sector employment; business and administration associate professionals, 2.8 percent; and science and engineering professionals, 1.9 percent. Customer services clerks account for 1.3 percent, general and keyboard clerks for 1.2 percent, administrative and commercial managers for 1.1 percent, and other clerical support workers for 0.5 percent.

Business and administration associate professionals, science and engineering professionals, and administrative and commercial managers are internally heterogeneous occupation groups. Their classification reflects exposure in reporting, documentation, analysis, coordination, workflow support, and related information processing functions at the two-digit occupation level, not uniform risk across all roles or tasks. This caveat is especially important for science and engineering professionals and managers, whose work varies considerably across disciplines, firms, and production settings.

Clerical occupations form the clearest core of this archetype because many of their tasks involve standardized documentation, scheduling, record-keeping, communication, reporting, and information processing. AI can increasingly perform or assist with these activities, but demand for the underlying functions is often tied to organizational budgets, managerial structures, and internal processing requirements rather than to markets in which lower costs generate substantial additional demand.

The greatest potential for direct labor-saving adjustment is concentrated in information processing, clerical, administrative, and analytical functions rather than in the lower-exposure physical work prevalent in agriculture, construction, transport, and much of informal employment.

Reorganize Occupations

Reorganize is the largest high-exposure archetype, accounting for 21.3 percent of private sector employment across six occupation groups. These occupations combine high exposure and constrained demand with continuing human necessity. Workers remain integral to production or service delivery even when AI raises productivity, but the amount or composition of labor required may change.

Sales workers are the largest occupation in this archetype and the main contributor to the aggregate Reorganize share, accounting for 10.6 percent of private sector employment. Many sales activities continue to depend on customer interaction, physical presence, trust, and real-time coordination, even when AI supports pricing, inventory management, customer targeting, transaction processing, and routine customer service.

Demand conditions determine their classification. Retail trade accounts for 71.4 percent of sales-worker employment. The sector-weighted elasticity estimate is $\eta = -0.850$, placing sales workers on the constrained-demand side of the $\eta = -1.000$ threshold. Given constrained household purchasing power and the necessity-linked character of much retail consumption, the sector profile implies limited scope for proportionate demand expansion. This places sales workers in Reorganize rather than Grow with AI.

Other Reorganize occupations include stationary plant and machine operators; cleaners and helpers; food preparation assistants; legal, social, and cultural professionals; and assemblers. Although these groups differ substantially in task content, they share the combination of continuing human necessity and limited demand responsiveness.

The implied adjustment mechanisms differ across occupations. In production and machine-operation work, AI-assisted scheduling, monitoring, process optimization, and workflow systems could reduce the labor required per unit of output. In service and professional occupations, AI could alter documentation, coordination, routine support, and task allocation without eliminating the need for human presence, judgment, accountability, or real-time response.

Reorganize is not an intermediate category between automation and growth. It identifies a distinct adjustment mechanism in which occupations persist but the amount or composition of labor required may change. Adjustment may emerge gradually through slower recruitment, changes in hours, task consolidation, weaker employment growth, or movement into different employment arrangements rather than immediate layoffs.

Grow with AI Occupations

Grow with AI occupations combine high exposure with sufficiently elastic demand under the framework. They account for 7.7 percent of private sector employment across six occupation groups, making this the smallest archetype.

The largest occupation group is food processing, woodworking, garment, and other craft and related trades workers, which accounts for 4.0 percent of private sector employment. The archetype also includes handicraft and printing workers; business and administration professionals; information and communications technology (ICT) professionals; ICT technicians; and street and related sales and service workers.

These assignments identify occupations in which lower effective costs may expand output, service use, or market reach. In business services and ICT, productivity gains may widen access to accounting, consultancy, software, technical support, and related services, particularly among small and medium-sized enterprises that currently underuse them. In craft and specialized production, AI-assisted design, customization, production planning, and digital distribution may expand access to niche or price-sensitive markets without eliminating an important role for specialized human labor.

The inclusion of craft and production occupations may appear counterintuitive because these jobs contain substantial physical content. Their placement in Grow with AI does not imply that AI can

automate the occupation as a whole. Rather, their C-AIOE values place them above the exposure threshold, and their demand elasticity inputs place them on the elastic-demand branch of the framework. Food processing, woodworking, garment, and related trades alone account for just over half of employment classified as Grow with AI.

These classifications should not be interpreted as forecasts of employment growth. They identify occupations for which the framework classifies demand as sufficiently responsive to offset lower labor requirements per unit of output. The Grow with AI share is concentrated in a limited set of craft and specialized production, business service, and ICT occupations.

Occupations near the elasticity threshold are especially sensitive to the cutoff and should be interpreted in light of the sensitivity analysis in Appendix B. In particular, the Grow with AI share rises substantially when the elasticity cutoff is relaxed.

Less Change Occupations

Less Change is the largest archetype, accounting for 58.7 percent of private sector employment across 20 occupation groups. These occupations fall below the C-AIOE threshold because current AI capabilities affect their core task content less directly.

The largest occupations in this category are market-oriented skilled agricultural workers, at 12.9 percent of private sector employment; drivers and mobile plant operators, 6.0 percent; personal service workers, 5.4 percent; laborers in mining, construction, manufacturing, and transport, 5.0 percent; agricultural, forestry, and fishery laborers, 4.3 percent; and metal, machinery, and related trades workers, 4.2 percent.

These occupations rely heavily on physical execution, interaction with people or objects, adaptation to changing environments, and real-time situational response. Their classification reflects the more limited reach of current AI capabilities into embodied and situated tasks.

Less Change does not mean AI-proof. Occupations in this archetype may still experience incremental task automation, AI-assisted planning or diagnostics, and changes in workflow or supervision. The classification indicates only that their current task content is less directly exposed than that of occupations assigned to the other archetypes. Advances in robotics, autonomous systems, logistics, and embodied AI could shift these boundaries over time.

The aggregate profile is dual: most private sector employment remains in Less Change occupations, and Reorganize accounts for the largest share of high-exposure employment. Section 5 examines how this distribution varies across workers, sectors, regions, formality status, and establishment size.

5. AI Adjustment Archetypes across Workers and the Economy

The aggregate distribution conceals substantial variation across workers, sectors, regions, and employment settings. These differences largely reflect how workers are distributed across occupations associated with the four archetypes.

Gender, Educational Attainment, and Age

Figure 2 reports the distribution of private sector employment across archetypes by gender, educational attainment, and age. Youth are defined as ages 15–29, prime-age workers as ages 30–54, and older workers as ages 55 and above.

Women are more concentrated than men in both Reorganize and Automation Risk occupations. Reorganize accounts for 25 percent of female employment, compared with 19 percent of male employment; Automation Risk accounts for 15 percent of female employment and 11 percent of male employment. Men, by contrast, are more concentrated in Less Change occupations, at 62 percent compared with 51 percent among women.

These differences reflect occupational composition. Women are more heavily represented in sales, especially retail sales, as well as in clerical, administrative, and service-related occupations. Many of these occupations combine high AI exposure with constrained demand or limited human necessity. For women, the framework points to reorganization within continuing sales, clerical, administrative, and service roles as a more prominent potential adjustment margin than occupational displacement alone.

Educational attainment shows a pronounced gradient, but the pattern differs across the high-exposure archetypes. Automation Risk rises sharply with education, accounting for 32 percent of tertiary-educated employment, compared with 15 percent among workers with secondary education and only a small share among those with less than secondary education. Reorganize follows a different pattern: it is largest among workers with secondary education, at 25 percent, compared with 20 percent among those with less than secondary education and 18 percent among tertiary-educated workers. Even so, tertiary-educated workers are substantially more concentrated in the high-exposure archetypes overall, reflecting their greater representation in formal cognitive, clerical, administrative, professional, and analytical occupations. Workers with less than secondary education are more concentrated in physical and manual occupations classified as Less Change.

Tertiary-educated workers also have the largest Grow with AI share, at 11 percent. Overall, higher education is associated with greater representation in high-exposure occupations, but not with a single adjustment mechanism. Educational attainment shapes where workers are located across exposed occupations with different demand and human necessity profiles.

Age differences are more modest. Youth have a somewhat larger Automation Risk share than prime-age workers, consistent with their greater representation in entry-level clerical and administrative roles. Reorganize accounts for 24 percent of youth employment and 22 percent of prime-age employment. Older workers are much more concentrated in Less Change occupations, which account for 76 percent of their employment, compared with 57 percent among prime-age workers and 53 percent among youth.

Lower current exposure among older workers reflects their concentration in Less Change occupations rather than stronger representation in AI-complementary work. More broadly,

differences by gender, education, and age reflect where these groups are located within Türkiye's private sector occupational structure.

Sectoral Distribution

Figure 3 reports the archetype distribution across NACE sectors. These are occupational composition results: sectoral differences reflect the mixes of occupations they employ, not measured differences in sector-level AI adoption.

Trade has the largest Reorganize share, at 56 percent. Its profile is driven by the concentration of sales workers in retail and related activities, where AI can support pricing, inventory management, customer targeting, transaction processing, and routine customer service, while human interaction and physical presence remain important. Trade accounts for 17 percent of private sector employment, making its large Reorganize component consequential for the aggregate distribution.

Professional services presents a markedly different profile. Automation Risk accounts for 43 percent of sector employment, Reorganize for 21 percent, and Grow with AI for 17 percent. The sector illustrates that high exposure need not imply a single adjustment mechanism. Exposed analytical and administrative functions may face greater potential for labor-saving adjustment, whereas professional and technical services may reorganize or fall on the Grow with AI branch depending on demand responsiveness and human necessity.

Administrative and support services also contain substantial shares of Automation Risk and Reorganize occupations, at 21 and 31 percent, respectively. The sector combines clerical and administrative functions with cleaning, support, and coordination-intensive activities, producing a mix of greater potential for direct labor-saving adjustment and reorganization within occupations that continue to require workers.

Manufacturing combines a sizable Reorganize share, at 24 percent, with a comparatively large Grow with AI share, at 21 percent. Its occupational structure includes machine operators, assemblers, craft workers, technical roles, and production support functions. This mix is consistent with different potential adjustment mechanisms associated with AI-assisted production, monitoring, design, scheduling, and workflow technologies. Some occupations may require fewer labor inputs per unit of output; others may benefit from expanded production or market reach. Manufacturing accounts for 23 percent of private sector employment, making these adjustment margins consequential in aggregate terms.

Accommodation and food services also have a substantial Reorganize component, at 31 percent. Food preparation, service, scheduling, and customer-facing activities continue to depend on human presence even where AI can assist with coordination, ordering, staffing, and routine support. Reorganization extends beyond office and administrative work to service occupations in which delivery remains human intensive.

Agriculture is classified entirely as Less Change. Construction, transport, health, and education are also dominated by Less Change occupations. Their occupational structures rely heavily on physical execution, interpersonal delivery, environmental adaptation, or real-time response. This

does not imply limited AI use within these sectors. Rather, their employment is concentrated in task bundles that current AI capabilities affect less directly.

Regional Distribution

Figure 4 reports archetype distributions across Türkiye's Nomenclature of Territorial Units for Statistics (NUTS-2) regions. For readability, regions are labeled by their commonly used lead province or city. The figure shows a clear metropolitan and industrial pattern: regions with larger formal service, trade, administrative, professional, and manufacturing sectors tend to have higher Reorganize shares, whereas Less Change dominates in regions with more agricultural and physical employment.

Tekirdağ has the largest Reorganize share, at 28 percent, followed by İstanbul at 25 percent; Bursa and Ankara at 24 percent; Gaziantep and Kocaeli at 23 percent; and Aydın, Konya, and İzmir at 22 percent. These regions concentrate sales, administrative, professional, coordination-intensive, and production support occupations in which human involvement remains necessary even as AI may raise productivity.

At the lower end of the Reorganize distribution, Ağrı, Van, Trabzon, Kastamonu, and several other regions are heavily concentrated in Less Change occupations. Their employment structures contain larger shares of agriculture, construction, transport, and other physical or situated work to which current AI capabilities are less directly applicable.

These regional differences reflect occupational and sectoral composition rather than measured variation in AI adoption. Metropolitan and industrial regions are more concentrated in exposed cognitive, administrative, sales, professional, and organized production work. Their Automation Risk shares vary substantially, underscoring that greater occupational exposure does not translate into a single adjustment mechanism.

Lower current exposure should not be interpreted as stronger preparedness. Regions with larger agricultural and informal employment bases may also have weaker access to training, employment services, digital infrastructure, and social insurance if AI capabilities extend further into physical and embodied work. The regional pattern points to two distinct challenges: managing reorganization and greater potential for direct labor-saving adjustment in metropolitan and industrial labor markets, and strengthening adjustment capacity in regions whose occupations are less exposed today but whose workers may have less institutional support.

Formality Status and Establishment Size

Figure 5 reports archetype distributions by formality status and establishment size. Formality is defined by social security registration in the worker's main job. Establishment-size categories are one-person establishments, micro establishments with 2–9 workers, small establishments with 10–49 workers, and medium-to-large establishments with 50 or more workers.

Formal workers are more concentrated than informal workers in both Automation Risk and Reorganize occupations. Reorganize accounts for 24 percent of formal employment, compared

with 15 percent of informal employment; Automation Risk accounts for 17 percent of formal employment and 3 percent of informal employment. Informal workers, by contrast, are concentrated overwhelmingly in Less Change occupations, which account for 76 percent of informal employment.

This divide reflects occupational sorting across Türkiye's dual labor market. Formal employment contains larger shares of clerical, administrative, professional, sales, and organized production support occupations. Informal employment is more concentrated in agriculture, construction, household services, transport, and other physical or situated work. Current AI capabilities reach the task content of formal employment more directly than the embodied and real-time tasks prevalent in informal work.

Lower current exposure among informal workers should not be interpreted as stronger protection. It reflects the occupations in which they are employed, but weaker attachment to formal labor market institutions may limit access to employer-provided training, public employment services, and social insurance if their occupational exposure rises.

Establishment size shows a related pattern. One-person establishments are most concentrated in Less Change, at 65 percent. They contain larger shares of self-employment, informal work, personal services, trades, transport, and other physical activities whose task content falls below the current exposure threshold.

Automation Risk rises with establishment size and reaches 22 percent among workers in medium-to-large establishments. Larger establishments employ more administrative, professional, analytical, coordination-intensive, and production support workers, many of whom are located in highly exposed occupations. Reorganize remains substantial across micro, small, and medium-to-large establishments, reflecting the widespread presence of sales, service, coordination, and production occupations in organized employment. The establishment-size gradient reflects differences in occupational structure rather than a direct relationship between establishment size and AI adoption.

Synthesis

Across worker groups and economic settings, the distribution of archetypes is shaped primarily by occupational location. Women, tertiary-educated workers, formal workers, and workers in metropolitan and industrial regions are more concentrated in exposed sales, clerical, administrative, professional, and production support occupations. Workers with less education, informal workers, workers in one-person establishments, and workers in agriculture-intensive regions are more concentrated in Less Change occupations.

Under current AI capabilities, the framework places greater potential for adjustment in formal cognitive, administrative, sales, professional, and organized production work than in much physical and informal employment. However, lower current exposure does not imply greater resilience. Workers in lower-exposure occupations may have weaker access to the institutions needed to manage future adjustment if AI reaches further into embodied and situated tasks.

Türkiye's distributional profile reflects the interaction of occupational structure with sectoral composition, regional economic geography, formality, establishment size, and demand conditions. Section 6 places this profile in comparative perspective.

6. Comparative Perspective and Value Added

Türkiye's archetype distribution differs from Richmond's (2026a) U.S. application in three main respects: a lower Automation Risk share, a smaller Grow with AI share, and a larger Less Change share. Reorganize remains the largest high-exposure archetype in both settings. Richmond's (2026b) EU application provides a second comparator, with a smaller Automation Risk share and a larger Reorganize share than in the United States. These comparisons are interpretive rather than harmonized decompositions of country differences because the applications differ in exposure measures, occupational classifications, employment coverage, demand elasticity inputs, and aggregation procedures. The observed gaps may reflect both economic structure and methodological design and should not be attributed solely to country characteristics.

Türkiye and Richmond's U.S. and EU Applications

Table 3 compares Türkiye's private sector archetype distribution with the distributions reported in Richmond's U.S. and EU applications. Automation Risk accounts for 12.3 percent of private sector employment in Türkiye, compared with 18 percent in the United States and 14 percent in the EU-27. Reorganize accounts for 21.3 percent in Türkiye, 24 percent in the United States, and 27 percent in the EU-27. Grow with AI represents 7.7 percent in Türkiye and 12 percent in both the United States and the EU-27. Less Change accounts for 58.7 percent in Türkiye, compared with 46 percent in the United States and 47 percent in the EU-27.

The comparison does not support the presumption that middle-income economies necessarily have larger Automation Risk shares. Türkiye's more notable differences are a smaller Grow with AI share and a substantially larger Less Change share. The EU profile lies between Türkiye and the United States on Automation Risk. Reorganize exceeds Automation Risk in all three applications.

Türkiye's lower Automation Risk share is consistent with its occupational structure. A substantial share of private sector employment remains outside the exposed clerical, administrative, and professional groups classified as Automation Risk and is instead concentrated in agriculture, construction, transport, manual trades, personal services, and other forms of physical or situated work. Richmond (2026b) similarly attributes Europe's smaller Automation Risk share relative to the United States partly to its greater employment weight in manufacturing, skilled trades, transport, care work, education, and public service occupations, where work is often physical, place-based, or tied to relatively fixed service volumes.

The smaller Grow with AI share indicates that relatively few high-exposure occupations in Türkiye meet the demand elasticity criterion. This pattern is consistent with more limited scope for demand expansion in activities tied to necessity-linked consumption, small-enterprise markets, or internal organizational demand. However, the comparison cannot separate these economic mechanisms from differences in data and measurement.

The larger Less Change share reflects the continued importance of occupations whose core tasks remain less directly exposed to current AI capabilities. It does not imply permanent insulation from technological change. Rather, it indicates that a large share of Türkiye's private sector workforce is concentrated in occupations involving physical execution, environmental adaptation, interpersonal delivery, and real-time response. Overall, the comparison points to a dual profile: substantial potential for reorganization within exposed occupations and a large lower-exposure employment base.

Interpreting Türkiye's Profile

Sales workers provide the clearest illustration of how demand responsiveness shapes Türkiye's archetype distribution. They account for 10.6 percent of private sector employment and are concentrated in retail and related activities. Their retail-heavy sectoral composition yields a sector-weighted elasticity that places them in Reorganize rather than Grow with AI. Given their large employment share, this classification is consequential for the aggregate Reorganize share.

The underlying mechanism is broader than sales. Where demand is not sufficiently responsive to offset lower labor requirements per unit of output, productivity gains may translate into weaker hiring, lower labor intensity, or changes in task organization even when human participation remains important.

Türkiye's large Less Change share, by contrast, reflects the continued weight of physical, embodied, and situated work. Agriculture, construction, transport, manual trades, personal services, and related occupations account for substantial shares of private sector employment.

Informality reinforces this pattern through occupational composition. Informal workers are concentrated in lower-exposure physical and situated work, although weaker access to training, employment services, and social insurance may reduce their capacity to adjust if exposure broadens into these occupations.

Türkiye's profile combines two distinct challenges. Formal, metropolitan, service sector, and production support employment is more concentrated in Reorganize and Automation Risk occupations under current AI capabilities. Workers and regions concentrated in Less Change face lower current exposure but may have weaker institutional capacity to respond if the range of affected tasks expands.

Value Added Relative to Aşık et al. (2026)

Aşık et al. (2026) apply the C-AIOE framework to Turkish labor force survey data and classify occupations by exposure and complementarity. Their approach identifies where AI may affect occupational tasks and whether those effects are more likely to augment or substitute for workers. The two analyses yield similar aggregate exposure shares despite differences in employment coverage. Aşık et al. report roughly 41 percent of total employment as high exposure, compared with about 41 percent of private sector employment in this paper before the demand elasticity and human necessity filters are applied.

The contribution of this paper is to distinguish potential adjustment mechanisms within that high-exposure group. Exposure and complementarity alone do not separate greater potential for direct labor-saving substitution, reorganization within continuing occupations, and employment expansion through demand growth. Adding demand elasticity and human necessity allocates high-exposure employment across Automation Risk, Reorganize, and Grow with AI.

Sales workers again illustrate the added role of demand responsiveness. Their interpersonal and customer-facing tasks may imply substantial complementarity because AI can augment some activities without eliminating the need for human interaction. Yet incorporating their retail-heavy sectoral composition and demand responsiveness places them in Reorganize rather than Grow with AI.

The same logic extends across occupations. A highly exposed occupation may continue to require human participation yet still face weaker hiring or lower labor intensity if productivity rises faster than demand. Where human necessity is limited, another highly exposed occupation may face greater potential for more direct labor-saving substitution. Where demand is sufficiently responsive, a third may fall on the Grow with AI branch.

For Türkiye, incorporating demand elasticity and human necessity assigns the largest high-exposure employment share to Reorganize. Relative to Richmond's (2026a) U.S. application, Türkiye has a larger Less Change share and a smaller Grow with AI share. Relative to the EU application, Türkiye has a substantially larger Less Change share, a smaller Grow with AI share, and a somewhat lower Automation Risk share.

Recent adoption-based evidence provides a useful but distinct perspective. Chandar and Klein Teeselink (2026) find across 41 countries that foreign affiliates of AI-adopting companies shift their workforce composition away from junior workers, with the decline in the junior share driven primarily by growth in senior employment and suggestive evidence of modest overall employment growth. This evidence is consistent with the possibility that important adjustment occurs within continuing occupations. However, it should not be interpreted as validation of the archetype classifications. Their analysis concerns realized adjustment among adopting multinational affiliates, whereas this paper provides a nationally representative occupation-level diagnostic of potential adjustment mechanisms.

7. Policy Implications

The archetype distribution points to differentiated policy priorities. Automation Risk occupations call for credible transition pathways; Reorganize occupations require support while workers remain employed and before adjustment becomes visible in unemployment or loss of formal employment; Grow with AI occupations highlight measures that can ease constraints on demand for AI-complementary services and capabilities; and Less Change occupations call for preparedness as technological reach expands. The substantially larger employment share in Reorganize than in Automation Risk makes early detection of restructuring especially important, before adjustment becomes visible as unemployment or loss of formal employment.

Supporting Transitions from Automation Risk Occupations

Automation Risk occupations are concentrated in clerical, administrative, customer service, record-keeping, and analytical support functions whose exposed tasks can increasingly be performed or assisted by AI. Adjustment may first appear through weaker recruitment, hiring freezes, outsourcing, or reduced demand for administrative support rather than abrupt layoffs. Policy should combine transition support with early monitoring of occupational labor demand.

Workers in these occupations may possess transferable organizational, communication, coordination, and problem-solving skills. Transition strategies should build on these capabilities and support movement into adjacent roles where interpersonal interaction, accountability, field presence, or real-time judgment remain important. Illustrative functions include customer relationship support, logistics coordination, compliance support, case management support, and other public-facing or coordination-intensive work. Appropriate transitions should be guided by observed vacancies, local demand, and workers' existing skills.

Even technically feasible transitions may face important behavioral barriers. Recent experimental evidence shows that perceived fit with a destination occupation, including occupational identity, can shape workers' willingness to reskill, and that information on wages and job opportunities is more effective when workers already perceive some fit with the alternative occupation (Delfino et al. 2026). Transition strategies should account not only for skill adjacency and observed vacancies, but also for workers' preferences, occupational identity, and perceived fit with destination roles.

Training should be linked to credible occupational transitions rather than confined to general digital skills. Short, modular programs can combine digital tool use with sector-specific knowledge, communication, service delivery, and coordination capabilities. Their effectiveness is likely to depend on career counseling, job matching, employer engagement, and clear links to actual opportunities.

Monitoring should focus particularly on entry-level vacancies, hiring into clerical and administrative occupations, and transitions out of these roles. The objective is to identify weakening demand early enough to support workers while they remain attached to formal employment. Recent evidence reinforces the importance of these margins. U.S. payroll data indicate that employment declines among young workers in highly exposed occupations have operated primarily through reduced hiring rather than increased separations (Brynjolfsson, Chandar, and Chen 2026). Cross-country adoption evidence, in turn, shows a declining share of junior employment and a rising share of senior employment (Chandar and Klein Teeselink 2026).

Managing Reorganization before Displacement

Reorganize occupations pose a prominent policy challenge: adjustment may begin while workers remain employed. These occupations combine high AI exposure with relatively low constructed demand responsiveness and high human necessity. AI-related productivity gains may alter hiring, task allocation, hours, advancement, and labor intensity even where human participation remains important to production or service delivery. Policies activated only after job loss may respond too late.

Reorganize employment is concentrated in sales occupations and also includes production support, food preparation, cleaning, machine operation, and professional occupations. Policy priorities fall into three areas: in-work adaptation, sector-specific monitoring, and continuity of protection.

First, training systems should help workers adapt to changing task bundles and use AI-enabled tools while expanding their capacity to perform more complex, interpersonal, supervisory, or coordination-intensive tasks. For sales and retail workers, illustrative areas include customer relationship management, digital merchandising, inventory and logistics coordination, and AI-supported customer service. For production support and coordination-intensive occupations, relevant areas may include workflow management, scheduling, quality control, compliance documentation, and process monitoring. These areas should be validated through employer and worker engagement rather than treated as predetermined training packages. Similar frictions may matter for in-work adaptation when changing task bundles alter the content of workers' roles, although the available evidence speaks more directly to occupational transitions than to reorganization within existing jobs.

Second, monitoring should focus on hours, task composition, staffing patterns, recruitment, and formal employment attachment in sectors where Reorganize occupations are concentrated, including retail, hospitality, food services, administrative support, building services, and manufacturing support. Employer engagement, combined with longitudinal labor market indicators, can help distinguish temporary fluctuations from more persistent restructuring and identify opportunities for in-work training or movement into adjacent roles.

Third, policy should reduce the risk that gradual restructuring weakens workers' access to formal protection. Where formal and informal work coexist, changing production models or employment relationships may increase movement into less protected arrangements. This is a potential risk rather than an observed outcome. Reducing gaps in social insurance coverage as workers move across employers and employment arrangements, preserving accrued entitlements, and maintaining access to employment services could limit losses in protection during adjustment.

Managing reorganization also requires earlier engagement from labor market institutions. The Turkish Employment Agency (İŞKUR) and related institutions could combine occupational analysis, employer engagement, in-work training, career guidance, and job matching while workers remain employed but face changing tasks or weakening recruitment prospects.

Expanding the Grow with AI Margin

The relatively small Grow with AI share highlights the importance of demand conditions, in addition to AI-related skills, in determining whether productivity gains can support employment expansion. Grow with AI occupations are concentrated in craft and specialized production, business services, and ICT.

A relevant policy objective is to identify constraints on firms' use of AI-complementary professional, technical, digital, and specialized production services and test measures to reduce them. Possible constraints include fixed costs, limited information, weak managerial capability, and difficulties reorganizing business processes, although the analysis does not identify which

constraints are binding in Türkiye. These constraints may limit the extent to which lower costs translate into wider service use, expanded output, and additional labor demand.

Possible instruments include advisory services, service vouchers, support for business process upgrading, and programs connecting small and medium-sized enterprises with professional, technical, digital, and specialized production providers. The objective should not be AI adoption for its own sake, but wider use of complementary capabilities that improve products, processes, market access, and organizational performance. These options should be piloted, evaluated, and adapted; the framework identifies potential demand responsiveness rather than the effectiveness of particular instruments or realized employment growth.

Preparing Less Change Occupations for Future Adjustment

The large Less Change archetype calls for preparedness rather than complacency. These occupations are concentrated in agriculture, construction, transport, manual trades, personal services, informal employment, one-person establishments, and lower-exposure regions. Their core tasks remain less directly exposed under current AI capabilities, but advances in robotics, autonomous systems, and AI-assisted equipment may expand the range of affected tasks over time.

Preparedness is especially important because lower current exposure is concentrated among groups and regions that may also have weaker access to training, employment services, and social insurance. Informal workers, workers in one-person establishments, and workers in agriculture-intensive regions may face greater adjustment difficulties if exposure rises before institutional capacity improves.

The classification does not identify the effectiveness of specific interventions, but it points to areas in which greater institutional reach could improve preparedness. Priorities include extending access to employment services and training beyond formal employer-based channels, improving outreach to informal workers and one-person establishments, strengthening the digital and physical infrastructure needed to deliver these services, and reducing barriers to employment service access and social insurance coverage among workers outside standard formal employment. Delivery models could include mobile services, community-based programs, and partnerships with local institutions adapted to regional labor market conditions.

Monitoring should also extend beyond occupations currently classified in the high-exposure archetypes. Agriculture, transport, logistics, construction, repair services, and other physical task activities could be tracked for the diffusion of robotics, autonomous technologies, AI-assisted equipment, and new workflow systems. Policy attention should remain focused on Automation Risk and Reorganize occupations, but lower-exposure sectors and regions should use the available time to strengthen adjustment capacity.

Strengthening Labor Market Adjustment Systems

The archetype-specific priorities point to three cross-cutting institutional functions.

First, Türkiye would benefit from stronger early warning systems. Monitoring should extend beyond unemployment and layoffs to occupational hiring, entry-level vacancies, hours, separations, task requirements, and movement across occupations and employment arrangements. Administrative data, labor force surveys, vacancy information, and employer engagement can provide complementary signals.

Second, employment services and training systems should become more anticipatory. İŞKUR and related institutions could use labor market information to identify adjacent occupations and emerging skill needs and connect career guidance, modular training, employer engagement, and job matching while workers remain employed.

Third, continuity of social protection and regional reach should be strengthened. Gradual restructuring may increase movement among formal employment, informal employment, self-employment, and other arrangements. Reducing gaps in social insurance coverage during transitions, preserving accrued entitlements, and maintaining access to employment services could mitigate losses in protection. In parallel, regions with lower current exposure need stronger access to training, employment services, and the digital and physical infrastructure required to deliver them before physical and embodied occupations become more exposed.

Table 4 synthesizes the principal adjustment mechanisms, priority workers and settings, and associated policy priorities for each archetype.

The archetype framework points to four connected policy margins: transition support where the potential for more direct labor-saving substitution is greater; in-work adaptation where the potential for reorganization is greater; demand-side measures where AI-complementary activities may expand; and preparedness where current exposure remains lower. The institutional challenge is to build labor market systems capable of detecting gradual and uneven adjustment, supporting workers before displacement, and preserving access to formal protection during transitions.

8. Conclusion

This paper applies the Richmond (2026a) AI Jobs Transition Framework to Türkiye's private sector labor market using microdata from the 2024 HLFS. The main finding is that Reorganize accounts for the largest share of high-exposure employment: 21.3 percent of private sector employment, compared with 12.3 percent in Automation Risk and 7.7 percent in Grow with AI. Less Change accounts for the remaining 58.7 percent. Among exposed occupations, the results point to greater potential for adjustment through reorganization of continuing work than through more direct labor-saving substitution. This ordering is sensitive to some alternative threshold choices, although Less Change remains the largest archetype across the illustrated specifications.

Türkiye's archetype distribution differs from Richmond's U.S. application. Türkiye has a lower Automation Risk share, a smaller Grow with AI share, and a substantially larger Less Change share. Reorganize is similar in magnitude across the two applications. The EU application provides a second comparator: Türkiye has a larger Less Change share, a smaller Grow with AI share, and a somewhat lower Automation Risk share than the EU-27. The applications differ

methodologically, so these comparisons should be interpreted as differences in archetype profiles rather than harmonized decompositions of country differences.

The archetypes also reveal marked distributional differences within Türkiye. Women, tertiary-educated workers, and formal workers are more concentrated in high-exposure occupations, although their distribution across Automation Risk, Reorganize, and Grow with AI differs. Less educated and informal workers are more concentrated in Less Change occupations. Similar differences across sectors, regions, and establishment sizes largely reflect occupational composition.

The paper's principal analytical contribution is to move beyond AI exposure and distinguish alternative potential adjustment mechanisms. Exposure alone identifies where AI can affect work, but not whether employment is more likely to face direct labor-saving pressure, reorganization within continuing occupations, or expansion through stronger demand. Incorporating demand elasticity and human necessity provides a transparent way to separate these possibilities within high-exposure employment.

Lower current exposure should not be interpreted as permanent protection. Many Less Change occupations remain below the exposure threshold because current AI capabilities affect physical, embodied, and real-time tasks less directly, but technological advances may extend further into these activities. The policy challenge is similarly differentiated: support credible transitions where the potential for more direct labor-saving substitution is greater; promote in-work adaptation where reorganization is more likely; reduce constraints on demand expansion where AI-complementary activities may grow; and strengthen adjustment capacity among lower-exposure workers and regions before technological reach expands further.

References

Acemoglu, Daron. 2024. "The Simple Macroeconomics of AI." NBER Working Paper 32487, National Bureau of Economic Research, Cambridge, MA.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–S340.

Acemoglu, Daron, and Pascual Restrepo. 2019a. "Artificial Intelligence, Automation, and Work." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 197–236. Chicago: University of Chicago Press.

Acemoglu, Daron, and Pascual Restrepo. 2019b. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2): 3–30.

Aşık, Güneş, Siddharth Hari, Efşan Nas Özen, and Dhushyanth Raju. 2026. "Artificial Intelligence and Labor Market Adjustment in Türkiye: Exposure and Complementarity." Social Policy and Labor Discussion Paper 2704, World Bank, Washington, DC.

Autor, David H. 2022. "The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty." NBER Working Paper 30074, National Bureau of Economic Research, Cambridge, MA.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.

Bessen, James. 2019. "Artificial Intelligence and Jobs: The Role of Demand." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 291–307. Chicago: University of Chicago Press.

Bick, Alexander, Adam Blandin, and David J. Deming. 2026. "The Rapid Adoption of Generative AI." *Management Science* 72 (10): 8440–8456.

Brynjolfsson, Erik, Bharat Chandar, and Ruyu Chen. 2026. "Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence." Working Paper, Stanford Digital Economy Lab, Stanford, CA.

Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2025. "Generative AI at Work." *Quarterly Journal of Economics* 140 (2): 889–942.

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J. Panton, Carlo Pizzinelli, Emma J. Rockall, and Marina Mendes Tavares. 2024. "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note 2024/001. International Monetary Fund, Washington, DC.

Cazzaniga, Mauro, Carlo Pizzinelli, Emma Rockall, and Marina M. Tavares. 2025. "Exposure to Artificial Intelligence and Occupational Mobility: A Cross-Country Analysis." *Economía LACEA Journal* 24 (1): 314–339.

Chandar, Bharat, and Bouke Klein Teeselink. 2026. "How Does AI Change Labor Demand? Evidence from 41 Countries." Working Paper, Stanford Digital Economy Lab, Stanford, CA.

Chen, Wilbur Xinyuan, Suraj Srinivasan, and Saleh Zakerinia. 2025. "Displacement or Complementarity? The Labor Market Impact of Generative AI." Working Paper 25-039, Harvard Business School, Boston, MA.

Delfino, Alexia, Andrea Garnero, Sergio Inferrera, Marco Leonardi, and Raffaella Sadun. 2026. "Unwilling to Reskill? Experimental Evidence from Real-World Jobseekers." NBER Working Paper 34633, National Bureau of Economic Research, Cambridge, MA.

Dell'Acqua, Fabrizio, Edward McFowland III, Ethan Mollick, Hila Lifshitz, Katherine C. Kellogg, Saran Rajendran, Lisa Krayer, François Candelon, and Karim R. Lakhani. 2026. "Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of Artificial Intelligence on Knowledge Worker Productivity and Quality." *Organization Science* 37 (2): 403–423.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock. 2024. "GPTs Are GPTs: Labor Market Impact Potential of LLMs." *Science* 384 (6702): 1306–1308.

Felten, Edward W., Manav Raj, and Robert Seamans. 2021. "Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses." *Strategic Management Journal* 42 (12): 2195–2217.

Gmyrek, Pawel, Janine Berg, Karol Kamiński, Filip Konopczyński, Agnieszka Ładna, Balint Nafradi, Konrad Rosłaniec, and Marek Troszyński. 2025. "Generative AI and Jobs: A Refined Global Index of Occupational Exposure." ILO Working Paper 140, International Labour Organization, Geneva.

Humlum, Anders, and Emilie Vestergaard. 2025. "Still Waters, Rapid Currents: Early Labor Market Transformation under Generative AI." NBER Working Paper 33777. Revised March 2026. National Bureau of Economic Research, Cambridge, MA.

Liu, Yan, He Wang, and Shu Yu. 2025. "Labor Demand in the Age of Generative AI: Early Evidence from the U.S. Job Posting Data." Policy Research Working Paper 11263, World Bank, Washington, DC.

Massenkoff, Maxim, and Peter McCrory. 2026. "Labor Market Impacts of AI: A New Measure and Early Evidence." Anthropic Economic Research, San Francisco, CA, March 5.

Noy, Shakked, and Whitney Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science* 381 (6654): 187–192.

Pizzinelli, Carlo, Augustus J. Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li. 2023. "Labor Market Exposure to AI: Cross-Country Differences and Distributional Implications." IMF Working Paper 2023/216, International Monetary Fund, Washington, DC.

Richmond, Alex Martin. 2026a. *The AI Jobs Transition Framework: Mapping AI's Near-Term Impact on Jobs*. San Francisco, CA: OpenAI Economic Research.

Richmond, Alex Martin. 2026b. *The AI Jobs Transition Framework for the EU*. San Francisco, CA: OpenAI Economic Research.

Webb, Michael. 2020. "The Impact of Artificial Intelligence on the Labor Market." https://ssrn.com/abstract=3482150 or http://dx.doi.org/10.2139/ssrn.3482150.

Table 1. Aggregate AI Adjustment Archetypes in Türkiye's Private Sector

Archetype	Number of occupation groups	Private sector employment share (%)	Three largest occupation groups
Automation Risk	7	12.3	Numerical and material recording clerks; business and administration associate professionals; science and engineering professionals
Reorganize	6	21.3	Sales workers; stationary plant and machine operators; cleaners and helpers
Grow with AI	6	7.7	Food processing, woodworking, garment, and other craft and related trades workers; handicraft and printing workers; business and administration professionals
Less Change	20	58.7	Market-oriented skilled agricultural workers; drivers and mobile plant operators; personal service workers

Notes: The occupation groups listed are the three largest within each archetype by employment share.

Table 2. Occupation-Level AI Adjustment Archetype Classification

ISCO-08 code	Occupation group	Private sector employment share (%)	C-AIOE	Demand elasticity (η)	Human necessity (H)
A.	**Automation Risk**				
43	Numerical and material recording clerks	3.5	5.202	–0.400	0.47
33	Business and administration associate professionals	2.8	4.821	–0.850	0.23
21	Science and engineering professionals	1.9	4.638	–0.850	0.16
42	Customer services clerks	1.3	5.293	–0.400	0.22
41	General and keyboard clerks	1.2	5.548	–0.367	0.31
12	Administrative and commercial managers	1.1	4.627	–0.683	0.27
44	Other clerical support workers	0.5	5.114	–0.317	0.16
B.	**Reorganize**				
52	Sales workers	10.6	4.942	–0.850	0.57
81	Stationary plant and machine operators	4.0	4.597	–0.400	0.84
91	Cleaners and helpers	3.0	4.495	–0.750	0.90
94	Food preparation assistants	1.9	4.621	–0.850	0.90
26	Legal, social, and cultural professionals	1.2	4.589	–0.967	0.52
82	Assemblers	0.8	4.654	–0.567	0.90
C.	**Grow with AI**				
75	Food processing, woodworking, garment, and other craft and related trades workers	4.0	4.524	–1.000	0.82
73	Handicraft and printing workers	1.4	4.765	–1.200	0.81
24	Business and administration professionals	1.3	4.931	–1.300	0.15
25	Information and communications technology professionals	0.6	5.216	–1.400	0.15
35	Information and communications technicians	0.2	4.849	–1.133	0.15
95	Street and related sales and service workers	0.2	4.897	–1.200	0.90
D.	**Less Change**				
61	Market-oriented skilled agricultural workers	12.9	4.152	–0.300	0.88

Table 2. Occupation-Level AI Adjustment Archetype Classification

ISCO-08 code	Occupation group	Private sector employment share (%)	C-AIOE	Demand elasticity (η)	Human necessity (H)
83	Drivers and mobile plant operators	6.0	4.128	–0.750	0.89
51	Personal service workers	5.4	4.349	–1.200	0.83
93	Laborers in mining, construction, manufacturing, and transport	5.0	4.108	–0.550	0.89
92	Agricultural, forestry, and fishery laborers	4.3	4.281	–0.217	0.90
72	Metal, machinery, and related trades workers	4.2	4.208	–0.650	0.90
71	Building and related trades workers, excluding electricians	4.1	3.936	–0.933	0.90
53	Personal care workers	2.7	4.304	–0.850	0.90
14	Hospitality, retail, and other services managers	2.1	4.177	–0.700	0.90
31	Science and engineering associate professionals	2.0	4.209	–0.633	0.41
13	Production and specialized services managers	1.9	4.184	–0.400	0.45
74	Electrical and electronics trades workers	1.6	3.954	–0.700	0.90
54	Protective services workers	1.5	3.761	–0.850	0.87
23	Teaching professionals	1.2	4.436	–1.167	0.81
96	Refuse workers and other elementary workers	1.0	4.240	–0.150	0.90
22	Health professionals	0.9	3.851	–0.567	0.90
32	Health associate professionals	0.7	4.315	–0.500	0.89
34	Legal, social, cultural, and related associate professionals	0.6	4.330	–0.817	0.32
11	Chief executives, senior officials, and legislators	0.5	4.080	–0.300	0.20
62	Market-oriented skilled forestry, fishery, and hunting workers	0.1	4.068	–0.550	0.90

Notes: C-AIOE denotes the complementarity-adjusted AI occupational exposure measure, η demand elasticity, and H human necessity. The elasticity reported for sales workers is the sector-weighted estimate used in the classification.

Table 3. AI Adjustment Archetype Distribution: Türkiye's Private Sector and Richmond's U.S. and EU Applications

Archetype	Türkiye private sector (%)	Richmond U.S. application (%)	Richmond EU-27 application (%)	Interpretation
Automation Risk	12.3	18	14	Lower in Türkiye than in the U.S. and EU-27, consistent with the larger employment share in lower-exposure agricultural, construction, transport, manual, and other physical occupations.
Reorganize	21.3	24	27	Reorganize exceeds Automation Risk in all three applications; in Türkiye, the share is driven substantially by sales workers and other occupations combining continuing human necessity with constrained demand.
Grow with AI	7.7	12	12	Smaller in Türkiye than in the U.S. and EU-27, indicating a more limited role for the elastic-demand branch under the implemented classification.
Less Change	58.7	46	47	Larger in Türkiye than in the U.S. and EU-27, consistent with the greater employment weight of agriculture, construction, transport, manual trades, personal services, and other physical or situated work.

Notes: U.S. application shares are from Richmond (2026a). EU-27 shares are from Richmond (2026b), which applies the framework to 2,609 ESCO occupations weighted by Eurostat 2025 employment. The Türkiye, U.S., and EU applications differ methodologically, so the table compares archetype profiles rather than providing a harmonized cross-country decomposition.

Table 4. Policy Priorities by AI Adjustment Archetype

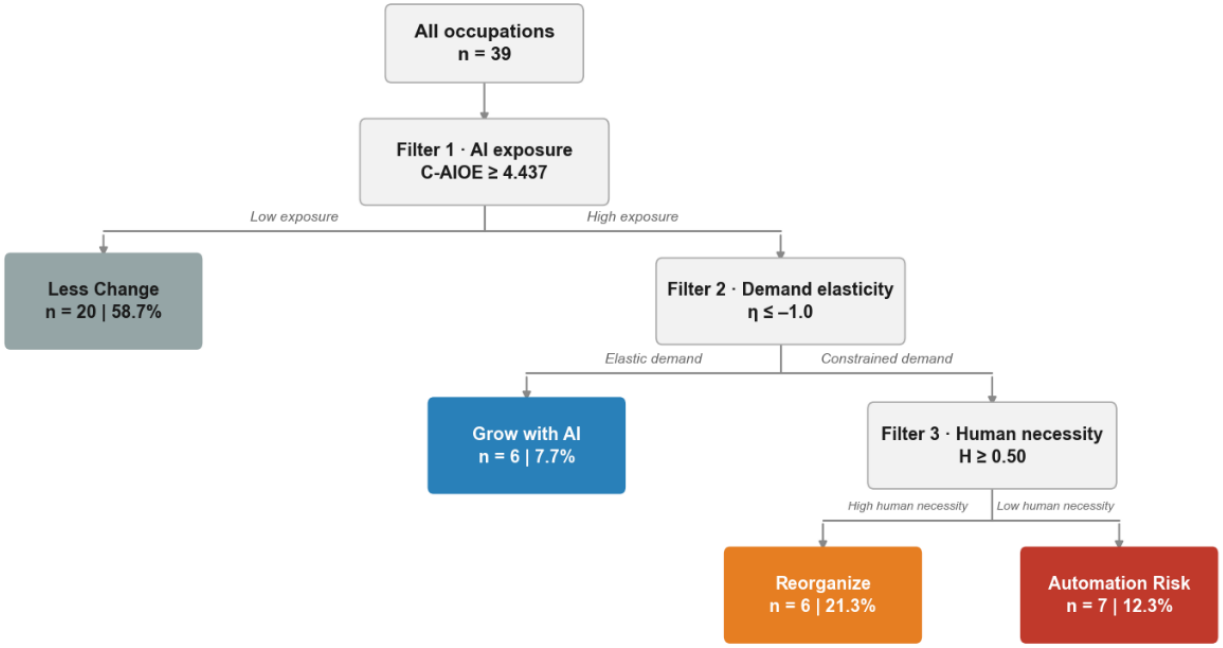
Archetype	Potential adjustment mechanism	Priority workers and settings	Policy priorities
Automation Risk	Greater potential for more direct labor-saving substitution of exposed tasks, with adjustment potentially appearing through weaker recruitment or declining demand for clerical, administrative, customer service, record-keeping, and analytical support functions.	Workers in exposed clerical, administrative, customer service, record-keeping, and analytical support occupations, particularly in metropolitan and industrial labor markets.	Build credible transition pathways into adjacent occupations with stronger human necessity; provide placement-linked, modular reskilling; account for occupational fit and worker preferences in transition design; strengthen career guidance, job matching, employer engagement, and early monitoring of occupational labor demand.
Reorganize	Changes in hiring, hours, task allocation, work organization, and labor intensity within occupations that continue to require workers, with possible weakening of formal employment attachment.	Sales and retail workers; production support occupations; food preparation, cleaning, and machine operation activities; selected professional occupations; sectors where formal and informal work coexist.	Support in-work adaptation and task upgrading; monitor recruitment, hours, staffing patterns, task composition, and formal employment attachment; strengthen employer engagement, employment services, and continuity of social protection across changing employment arrangements.
Grow with AI	Productivity gains lower effective costs and may expand demand for AI-complementary goods and services, potentially supporting employment expansion.	Craft and specialized production, business services, and information and communications technology occupations; small and medium-sized enterprises that underuse professional, technical, digital, and specialized production services.	Identify and reduce barriers to firms' use of complementary services; support business process upgrading, managerial capability, data use, and market access; pilot and evaluate instruments such as advisory services, service vouchers, and provider-linkage programs.

Table 4. Policy Priorities by AI Adjustment Archetype

Archetype	Potential adjustment mechanism	Priority workers and settings	Policy priorities
Less Change	Lower current exposure, with potential future adjustment as AI extends further into physical, embodied, and situated work, often among workers and settings with weaker institutional support.	Agriculture, construction, transport, manual trades, personal services, informal workers, one-person establishments, and lower-exposure regions.	Use the current lower-exposure period to strengthen preparedness; expand access to training, employment services, digital and physical delivery infrastructure, and social insurance; improve outreach to informal workers and one-person establishments; monitor the diffusion of robotics, autonomous systems, AI-assisted equipment, and related technologies.

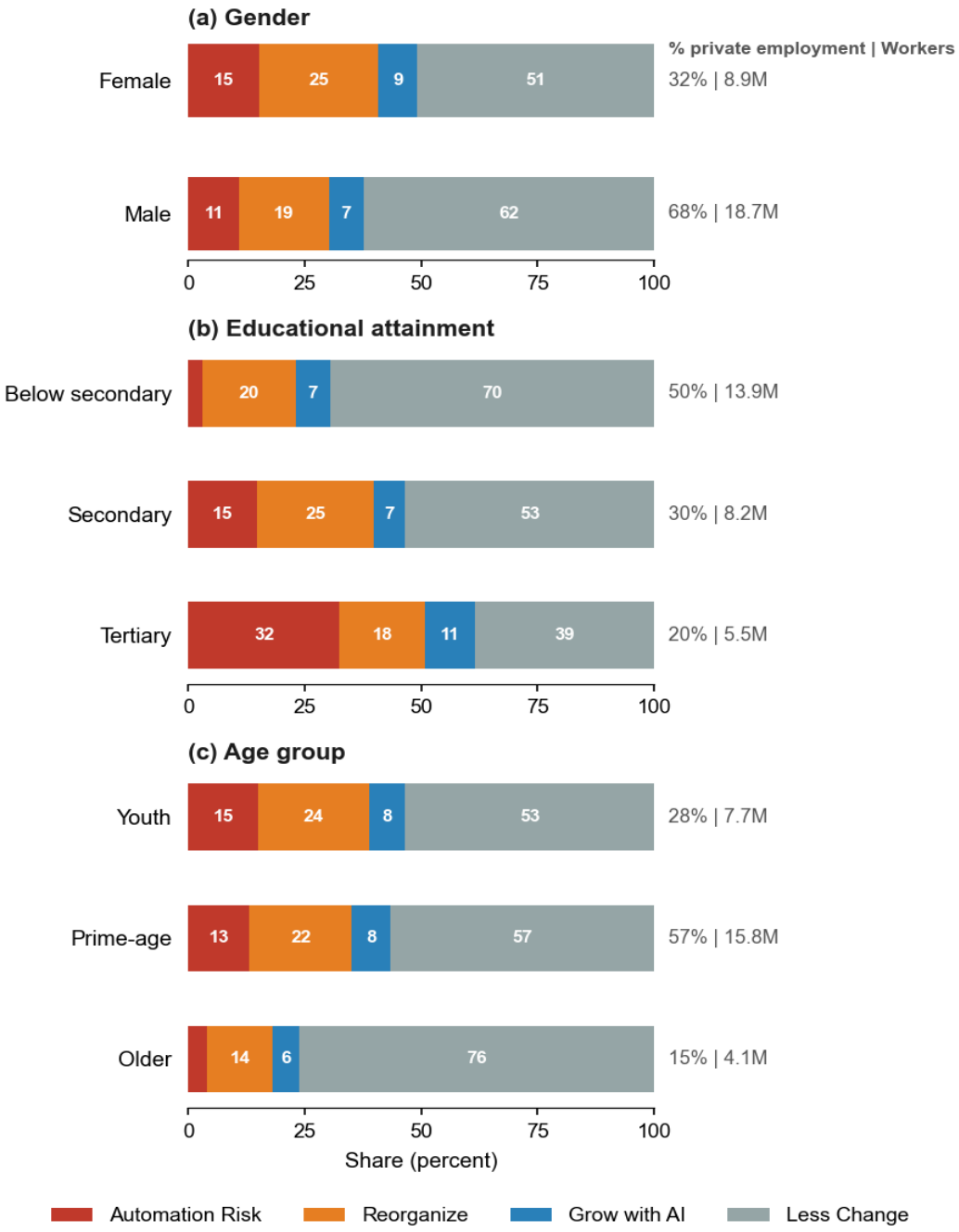
Notes: Adjustment mechanisms and policy priorities are illustrative implications of the archetype classification, not forecasts of realized employment change or evidence on the effectiveness of specific interventions.

Figure 1. AI Adjustment Archetype Classification Tree for Türkiye's Private Sector



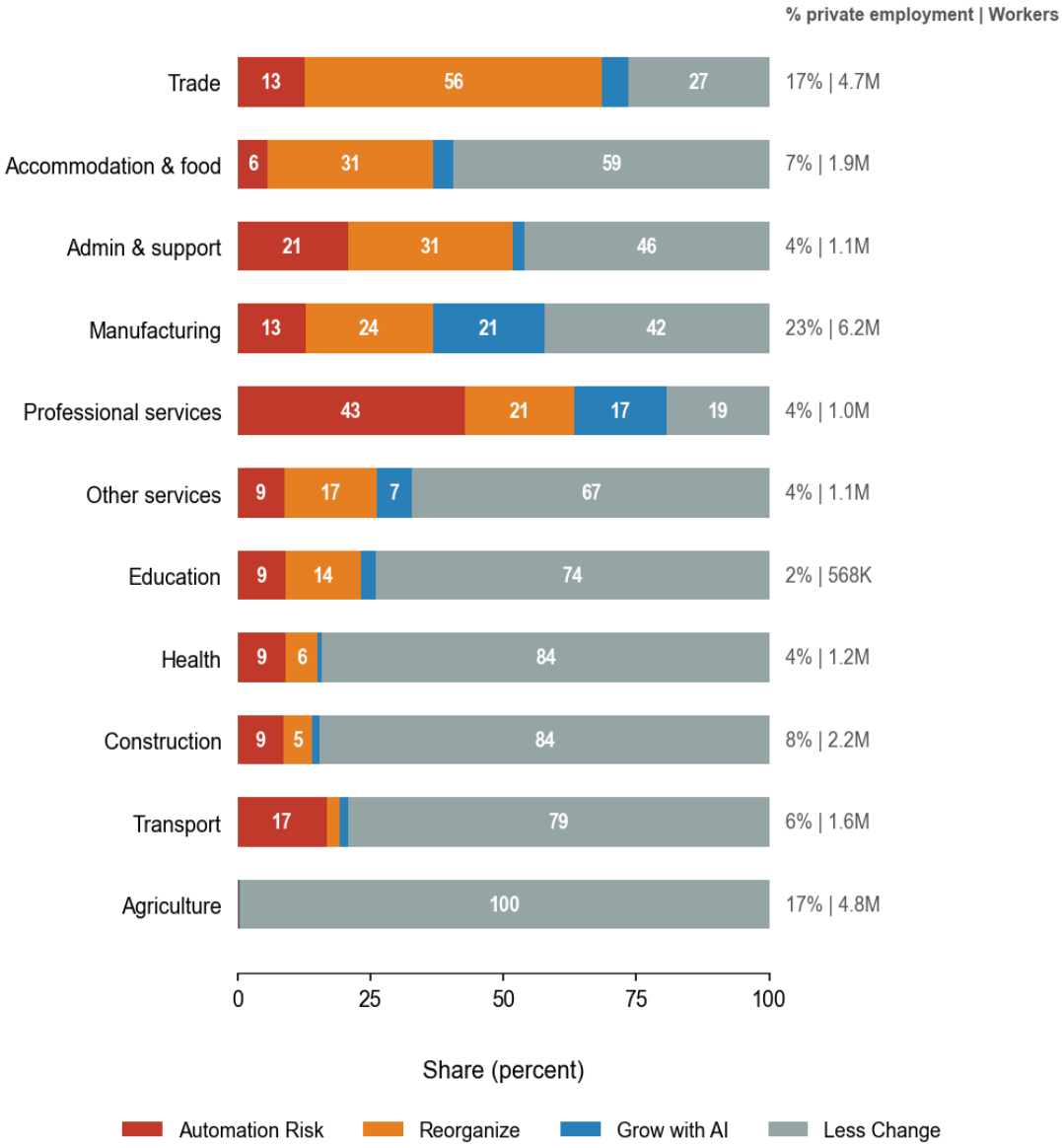
Notes: This figure shows the sequential classification of ISCO-08 two-digit occupation groups into the four AI adjustment archetypes. Percentages are weighted shares of total private sector employment. C-AIOE denotes the complementarity-adjusted AI occupational exposure measure, η demand elasticity, and H human necessity.

Figure 2. AI Adjustment Archetypes by Gender, Educational Attainment, and Age



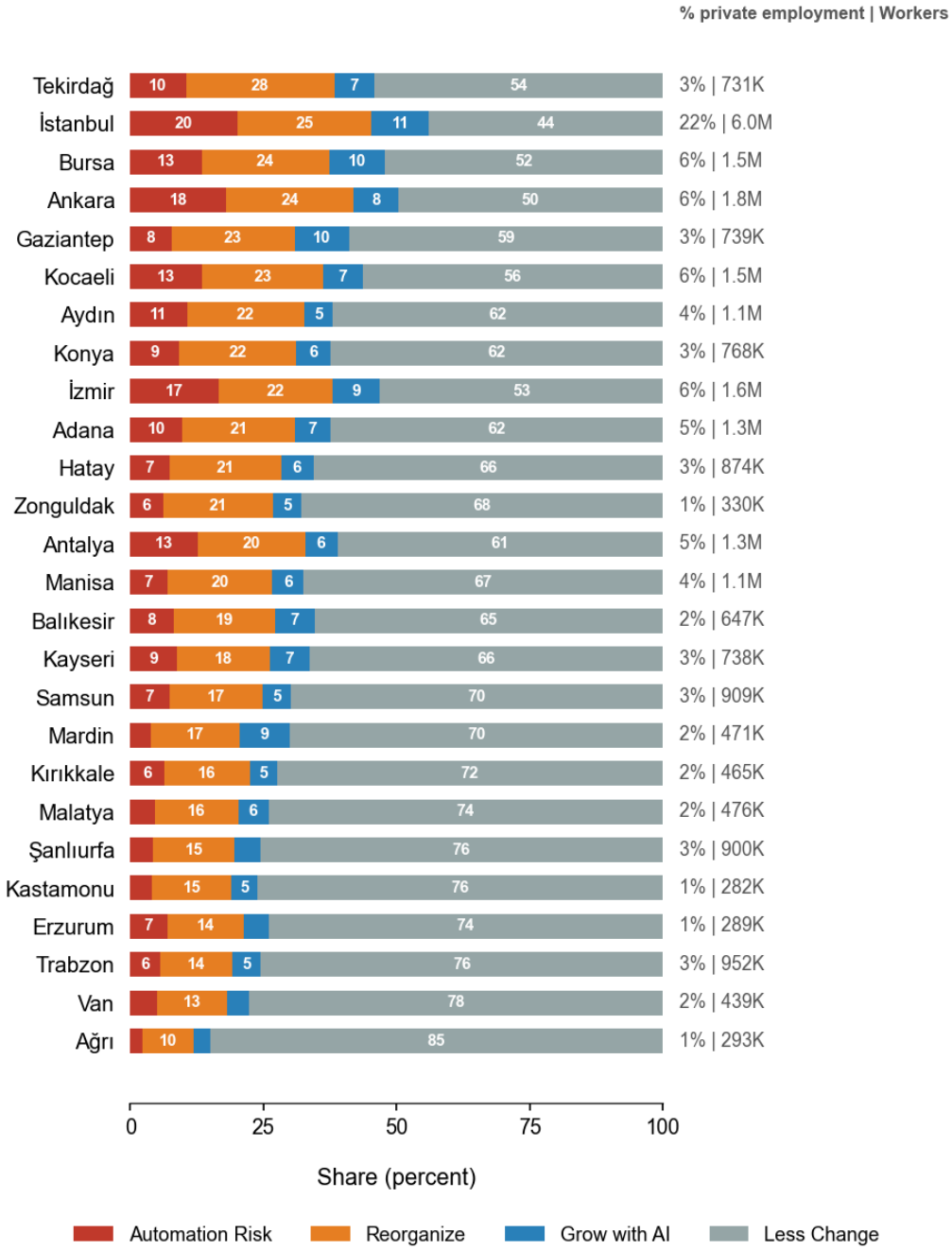
Notes: This figure shows the distribution of private sector employment across AI adjustment archetypes by gender, educational attainment, and age group. Youth are ages 15–29, prime-age workers ages 30–54, and older workers ages 55 and above. Bar segments of 5 percent or greater are labeled. The figures on the right report each group's share of total private sector employment and corresponding weighted number of workers.

Figure 3. AI Adjustment Archetypes by Sector



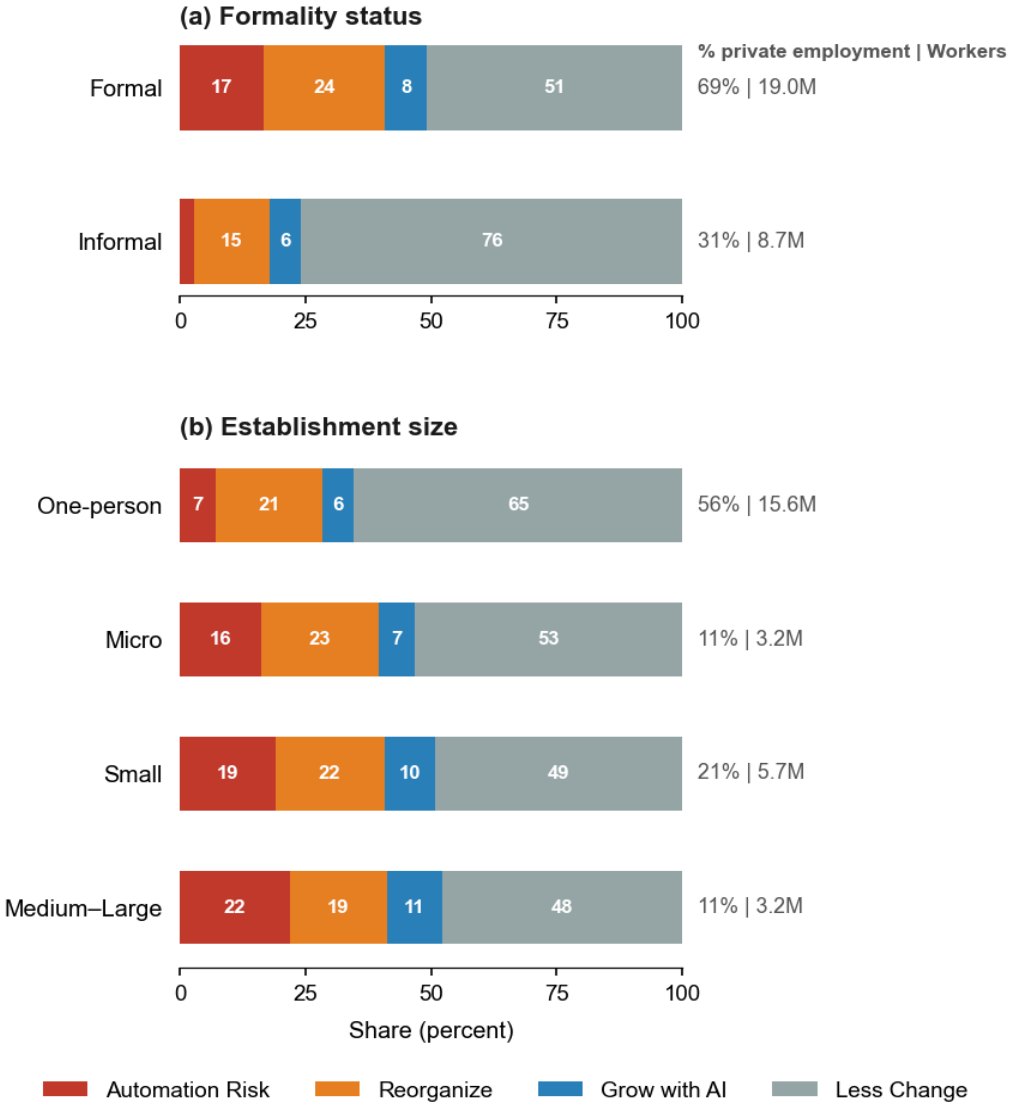
Notes: This figure shows the distribution of private sector employment across AI adjustment archetypes by sector. Sectors are ordered by their Reorganize share. Bar segments of 5 percent or greater are labeled. The figures on the right report each sector's share of total private sector employment and corresponding weighted number of workers.

Figure 4. AI Adjustment Archetypes by NUTS-2 Region



Notes: This figure shows the distribution of private sector employment across AI adjustment archetypes by NUTS-2 region. Region labels use the commonly used lead province or city name rather than the full NUTS-2 regional title. Regions are ordered by their Reorganize share. Bar segments of 5 percent or greater are labeled. The figures on the right report each region's share of total private sector employment and corresponding weighted number of workers.

Figure 5. AI Adjustment Archetypes by Formality Status and Establishment Size



Notes: This figure shows the distribution of private sector employment across AI adjustment archetypes by formality status and establishment size. Formality is defined by social security registration in the worker's main job. Establishment-size categories are one-person, micro (2–9 workers), small (10–49 workers), and medium-to-large (50 or more workers). Bar segments of 5 percent or greater are labeled. The figures on the right report each group's share of total private sector employment and corresponding weighted number of workers.

Appendix A. Construction of the Demand Elasticity and Human Necessity Measures

This appendix provides the technical documentation underlying the demand elasticity inputs and human necessity scores summarized in Section 3. It reports the occupation profiles, elicitation prompts, implementation settings, run-level diagnostics, source variables, normalization procedures, reconciliation rules, crosswalk procedures, and aggregation calculations used to construct the measures.

Demand Elasticity Inputs

Standardized Occupation Profiles

A standardized profile was prepared for each International Standard Classification of Occupations, 2008 revision (ISCO-08) two-digit occupation group. Each profile contained:

1. The official International Labour Organization (ILO) occupation title and definition
2. Five representative tasks adapted to Türkiye's private sector context
3. A description of the associated output or service whose demand responsiveness was to be assessed.

The profiles followed a common structure. For occupations producing final goods or services, the demand object was the relevant consumer or business market. For occupations providing intermediate, professional, technical, or internal organizational services, the demand object was firms' or organizations' use of those services. The profiles also incorporated market characteristics relevant to Türkiye, including its middle-income setting, high density of small and medium-sized enterprises, substantial informality, and large agricultural workforce.

The representative tasks and output or service descriptions were prepared by condensing the official ISCO-08 titles, definitions, and task lists into a standardized format adapted to the Turkish private sector context. One author prepared all 39 profiles. Profiles were fixed before elicitation and not revised across runs.

Elicitation Protocol

The elicitation used Claude Sonnet 4.6 through the Anthropic Messages Application Programming Interface (API). A fixed prompt and profile structure were applied across occupations. The model estimated the demand response to a 10 percent reduction in effective cost, expressed it as an own-price elasticity, assigned a qualitative elasticity category, and provided a concise rationale grounded in Türkiye's market structure. The prompt explicitly distinguished demand for the occupation's output or service from demand for labor.

Box A1 reproduces the implemented system instruction, occupation-profile structure, and user prompt.

Box A1. Prompt Used to Elicit Occupation-Level Demand Elasticity

System Instruction

You are an applied labor economist estimating own-price demand elasticity for Turkish private sector occupations.

You will be given a structured occupation profile containing the ISCO-08 title, ILO definition, core tasks, and the primary output of the occupation in the Turkish market context. Your task is to estimate how much demand for the occupation's output changes when its price falls by 10 percent.

This is a demand elasticity question only. Do not consider AI capabilities or AI adoption, changes in the number of workers, or supply-side effects.

Focus only on the following question: if the buyer price of this occupation's output fell by 10 percent, how much more of it would buyers want over two to three years?

Apply the following Turkish market context throughout: Türkiye is a middle-income economy; its private sector is dominated by small and medium-sized enterprises; informality is substantial; household purchasing power is constrained; necessities account for a large share of household budgets; latent demand may exist for professional and information and communications technology services; and institutional purchasers play important roles in health and education.

Make the elasticity more negative when lower prices are likely to unlock demand among households or firms currently priced out, increase frequency of use or service quality, or expand demand for discretionary, customizable, or export-oriented output. Keep the elasticity closer to zero when demand is constrained by necessity, physical volume limits, fixed production requirements, public budgets, reimbursement systems, regulation, or overall production volume.

The response must be valid JavaScript Object Notation (JSON) only, with no preamble or markdown. Respond consistently when asked the same question. Estimates should reflect stable economic reasoning about Turkish demand structure.

Standardized Occupation-Profile Structure

Each profile contains:

- ISCO-08 code
- Occupation title
- Official ISCO-08 definition
- Five representative tasks
- A description of the occupation's primary output or service in the Turkish market.

These fields are fixed for each occupation and are identical across all three runs.

User Prompt

OCCUPATION PROFILE
ISCO-08 code: {code}
Title: {title}
ILO definition: {definition}
Core tasks: {core_tasks}
Primary output in the Turkish market: {turkish_output}

QUESTION
Suppose the buyer price of this occupation's output falls by 10 percent because production costs fall, while quality and scope remain unchanged. Estimate only the demand response for the occupation's output, not AI exposure and not demand for workers. If this occupation's output became 10 percent cheaper, how much more of it would Turkish households, firms, or institutions want over the next two to three years?

REQUIRED JSON OUTPUT
elasticity: float, expressed as a negative value
bucket: elastic, moderate, or inelastic
demand_type: discretionary, mixed, or necessity
primary_constraint: latent_demand, necessity, budget, regulatory, or production_volume
rationale: two sentences explaining what drives demand for the output in Türkiye and why price sensitivity is high or low

BUCKET DEFINITIONS
Elastic: $|\eta| \geq 1.0$
Moderate: $0.5 \leq |\eta| < 1.0$
Inelastic: $|\eta| < 0.5$

Each directly elicited occupation group was evaluated in three independent API calls using the same profile and prompt. The final occupation-level elasticity was calculated as

$$\eta_o = \frac{1}{3}\sum_{r=1}^{3} \eta_{or},$$

where η_{or} is the elasticity estimate for occupation o in run r.

Run-to-run dispersion was calculated as

$$R_o = \max_r(\eta_{or}) - \min_r(\eta_{or}).$$

Table A1 summarizes the implementation protocol.

Table A1. Implementation Protocol for the Demand Elasticity Elicitation

Element	Implemented procedure
Unit of assessment	ISCO-08 two-digit occupation group
Model	Claude Sonnet 4.6
Full model identifier	`claude-sonnet-4-6`
Access period	Early May 2026; exact dates were not retained
Interface	Anthropic Messages API
Occupation profile	Official ISCO-08 title and definition; five representative tasks; description of the associated output or service
Market conditioning	Türkiye's income level, small and medium-sized enterprise structure, informality, agricultural employment, purchasing-power constraints, and occupation-specific demand conditions
Prompted cost change	10 percent reduction in the effective cost of the occupation's output or service
Requested output	Numerical η, qualitative elasticity category, demand type, primary constraint, and concise rationale
Runs per directly elicited occupation	3
Seed treatment	The API did not provide a fixed random seed
Output validation rule	Response parsed as JSON; elasticity converted to numeric; positive elasticity values rejected rather than sign-reversed
Treatment of malformed or incomplete outputs	Parsing or field-extraction failures recorded as missing rather than automatically retried
Selective rerunning	None in the original noninteractive pass
Final estimate	Arithmetic mean across three runs
Stability diagnostic	Maximum minus minimum estimate across runs
Departure from occupation-level protocol	Sector-disaggregated, employment-weighted estimate for sales workers

Notes: The same profile structure, prompt, sign convention, qualitative categories, and required output fields were applied across the 38 directly elicited occupation groups. Sales workers were the only occupation group receiving sector-disaggregated treatment.

The output validation rule was subsequently revised to reject positive elasticity estimates rather than reverse their sign. The full three-run elicitation was rerun under the corrected rule. No positive elasticity outputs occurred, and the resulting occupation-level means remained within the documented run-to-run stability range, suggesting that the earlier sign-reversal logic did not materially affect the reported elasticity inputs.

Run-Level Estimates and Stability

Table A2 reports the three run-level estimates, their arithmetic mean, and the run range for each directly elicited occupation group.

Table A2. Run-Level Demand Elasticity Inputs and Stability

ISCO-08 code	Occupation group	Run 1	Run 2	Run 3	Three-run mean	Run range	Position relative to $\eta = -1.000$ cutoff
11	Chief executives, senior officials, and legislators	–0.300	–0.300	–0.300	–0.300	0.00	Inelastic
12	Administrative and commercial managers	–0.700	–0.700	–0.650	–0.683	0.05	Inelastic
13	Production and specialized services managers	–0.400	–0.400	–0.400	–0.400	0.00	Inelastic
14	Hospitality, retail, and other services managers	–0.700	–0.700	–0.700	–0.700	0.00	Inelastic
21	Science and engineering professionals	–0.850	–0.850	–0.850	–0.850	0.00	Inelastic
22	Health professionals	–0.550	–0.550	–0.600	–0.567	0.05	Inelastic
23	Teaching professionals	–1.100	–1.200	–1.200	–1.167	0.10	Elastic
24	Business and administration professionals	–1.300	–1.300	–1.300	–1.300	0.00	Elastic
25	Information and communications technology professionals	–1.400	–1.400	–1.400	–1.400	0.00	Elastic
26	Legal, social, and cultural professionals	–0.950	–1.100	–0.850	–0.967	0.25	Inelastic
31	Science and engineering associate professionals	–0.650	–0.650	–0.600	–0.633	0.05	Inelastic
32	Health associate professionals	–0.550	–0.550	–0.400	–0.500	0.15	Inelastic
33	Business and administration associate professionals	–0.850	–0.850	–0.850	–0.850	0.00	Inelastic
34	Legal, social, cultural, and related associate professionals	–0.850	–0.850	–0.750	–0.817	0.10	Inelastic
35	Information and communications technicians	–1.100	–1.100	–1.200	–1.133	0.10	Elastic
41	General and keyboard clerks	–0.350	–0.350	–0.400	–0.367	0.05	Inelastic
42	Customer services clerks	–0.400	–0.400	–0.400	–0.400	0.00	Inelastic
43	Numerical and material recording clerks	–0.400	–0.400	–0.400	–0.400	0.00	Inelastic
44	Other clerical support workers	–0.300	–0.350	–0.300	–0.317	0.05	Inelastic
51	Personal service workers	–1.200	–1.200	–1.200	–1.200	0.00	Elastic
53	Personal care workers	–0.850	–0.850	–0.850	–0.850	0.00	Inelastic
54	Protective services workers	–0.850	–0.850	–0.850	–0.850	0.00	Inelastic
61	Market-oriented skilled agricultural workers	–0.300	–0.300	–0.300	–0.300	0.00	Inelastic

Table A2. Run-Level Demand Elasticity Inputs and Stability

ISCO-08 code	Occupation group	Run 1	Run 2	Run 3	Three-run mean	Run range	Position relative to $\eta = -1.000$ cutoff
62	Market-oriented skilled forestry, fishery, and hunting workers	–0.550	–0.550	–0.550	–0.550	0.00	Inelastic
71	Building and related trades workers	–1.100	–0.850	–0.850	–0.933	0.25	Inelastic
72	Metal, machinery, and related trades workers	–0.650	–0.650	–0.650	–0.650	0.00	Inelastic
73	Handicraft and printing workers	–1.200	–1.200	–1.200	–1.200	0.00	Elastic
74	Electrical and electronics trades workers	–0.700	–0.650	–0.750	–0.700	0.10	Inelastic
75	Food processing, woodworking, garment, and other craft and related trades workers	–1.050	–1.100	–0.850	–1.000	0.25	Elastic
81	Stationary plant and machine operators	–0.400	–0.400	–0.400	–0.400	0.00	Inelastic
82	Assemblers	–0.550	–0.550	–0.600	–0.567	0.05	Inelastic
83	Drivers and mobile plant operators	–0.750	–0.750	–0.750	–0.750	0.00	Inelastic
91	Cleaners and helpers	–0.750	–0.750	–0.750	–0.750	0.00	Inelastic
92	Agricultural, forestry, and fishery laborers	–0.200	–0.250	–0.200	–0.217	0.05	Inelastic
93	Laborers in mining, construction, manufacturing, and transport	–0.550	–0.550	–0.550	–0.550	0.00	Inelastic
94	Food preparation assistants	–0.850	–0.850	–0.850	–0.850	0.00	Inelastic
95	Street and related sales and service workers	–1.200	–1.200	–1.200	–1.200	0.00	Elastic
96	Refuse workers and other elementary workers	–0.150	–0.150	–0.150	–0.150	0.00	Inelastic

Notes: The final column reports the occupation's position relative to the $\eta = -1.0$ demand elasticity cutoff only. Archetype assignment also depends on AI exposure and, where relevant, human necessity.

Across the 38 directly elicited occupation groups, the mean run range was 0.04, the median was 0.00, and the maximum was 0.25. Estimates were identical across all three runs for 23 occupations. Run-level estimates fell on both sides of the $\eta = -1.0$ classification threshold for three occupations.

The arithmetic mean, rather than the median or modal value, was used consistently in the final data set. All three runs were populated for every directly elicited occupation group, and no occupation required a selective rerun because of missing or malformed output. The implemented code did not automatically retry malformed responses, but no missing or malformed outputs appear in the completed data set.

These diagnostics assess numerical stability under repeated application of the procedure; they do not validate the constructed inputs against observed Turkish demand elasticities.

Sector-Disaggregated Treatment of Sales Workers

Sales workers receive a sector-disaggregated elasticity because the occupation group is large and spans sectors with materially different demand objects and demand conditions. A single occupation-level profile is poorly suited to representing the demand response relevant to the group as a whole.

The four sector categories are

1. **Retail trade:** the Statistical Classification of Economic Activities in the European Community (NACE) 47, retail trade except motor vehicles and motorcycles
2. **Wholesale trade:** NACE 46, wholesale trade except motor vehicles and motorcycles
3. **Food and beverage services:** NACE 56, food and beverage service activities
4. Remaining sectors employing sales workers.

The remaining sectors category covers sales workers distributed across other NACE activities. Its largest components are NACE 45, wholesale and retail trade and repair of motor vehicles and motorcycles, and NACE 10, manufacture of food products.

The sales-worker elasticity is calculated as

$$\eta_{52} = \sum_{s} w_{52,s}\, \eta_{52,s},$$

where $w_{52,s}$ is sector s's share of weighted sales-worker employment and $\eta_{52,s}$ is the corresponding sector-specific elasticity.

Each sector-specific elasticity was constructed using three independent API calls under the same prompt structure, model, market conditioning, validation procedure, and averaging rule applied to the directly elicited occupation groups. The remaining sectors value was elicited directly rather than derived from the other sector-specific values.

The sector-specific profiles adapted the base ISCO 52 profile to the demand context of each sector:

- Individual-consumer sales in retail trade
- Business-to-business bulk sales in wholesale trade
- Counter and order sales in food and beverage services
- A heterogeneous residual profile for remaining sectors, including motor-vehicle sales and food manufacturing.

Table A3 reports the sector-specific estimates, employment weights, and calculation of the sector-weighted elasticity.

Table A3. Sector-Weighted Demand Elasticity for Sales Workers

NACE activity	Employment share within ISCO 52 (%)	Run 1	Run 2	Run 3	Sector-specific mean η	Weighted contribution
Retail trade	71.4	–0.850	–0.850	–0.850	–0.850	–0.6070
Wholesale trade	8.9	–0.700	–0.700	–0.700	–0.700	–0.0624
Food and beverage services	5.3	–1.200	–1.200	–1.200	–1.200	–0.0635
Remaining sectors	14.4	–0.750	–0.850	–0.850	–0.817	–0.1175
Total	**100.0**					**–0.8504**

Notes: Employment shares are calculated among sales workers in the final HLFS analytical sample using unrounded survey-weighted values. Weighted contributions and the total elasticity are calculated using unrounded employment shares and sector-specific elasticity means. The total elasticity of $\eta = -0.8504$ is reported as $\eta = -0.850$ when rounded to three decimal places.

The resulting employment-weighted elasticity is $\eta = -0.8504$. Retail trade accounts for 71.4 percent of sales-worker employment and carries the largest weight in the estimate. This estimate replaces an earlier provisional value that had not been generated using the implemented three-run protocol. Both values lie above the $\eta = -1.000$ threshold, so the revised estimate does not change the sales-worker classification.

The sector-disaggregated treatment was introduced after review of the initial occupation-level result rather than specified in advance. The decision reflected the large employment share of sales workers, their concentration in retail trade, and the marked differences in demand objects and conditions across their employing sectors. No other occupation received sector-disaggregated treatment. The treatment is a targeted modeling adjustment rather than a general prespecified rule.

Interpretation and Limitations

The demand elasticity inputs are reproducible conditional on the standardized occupation profiles, prompt, model version, run design, output validation rules, and aggregation procedures. They are not estimated from observed price and quantity responses and should be interpreted as structured occupation-level classification inputs representing relative demand responsiveness.

The inputs may be sensitive to the definition of the relevant demand object, profile construction, prompt wording, model version, and Türkiye-specific contextual assumptions. The procedure also abstracts from firm-level variation in technology adoption, market power, cost pass-through, product quality, and organizational change. Aggregation at the ISCO-08 two-digit level may mask important differences across sectors, firms, tasks, regions, and employment arrangements.

The sector-disaggregated treatment of sales workers introduces an additional modeling choice because demand responsiveness is constructed by employing sector and aggregated using the Household Labor Force Survey (HLFS) sectoral distribution, whereas other occupations receive occupation-level estimates. It addresses one consequential source of within-occupation heterogeneity but does not resolve aggregation concerns more generally.

Human Necessity Scores

O*NET Inputs and Analytical Sample

The human necessity score is constructed from the Occupational Information Network (O*NET) 29.0 occupational data using the two channels summarized in Section 3: physical execution and live care and teaching.

A third candidate channel, licensed or certified judgment, was considered during development but is excluded from the baseline construction because O*NET coverage of the relevant certification item is incomplete. Certification-importance values are available for 516 of the 879 detailed O*NET–Standard Occupational Classification (SOC) records. The remaining 363 lack a value because the item was introduced later and coverage expanded through subsequent resurveying, rather than because certification is known to be irrelevant to those occupations. Unavailable coverage cannot be distinguished from a genuine absence of certification requirements, so the certification channel is excluded rather than coded as zero or imputed.

The O*NET 29.0 source files contain 879 detailed O*NET-SOC occupation records. All 879 have valid values for the physical-execution and live-care-and-teaching elements used in the implemented composites.

The supplementary crosswalk contains 879 detailed O*NET-SOC records corresponding to 763 unique six-digit SOC occupations. Sixty-four six-digit SOC codes are represented by more than one detailed O*NET variant. Detailed variants associated with the same six-digit SOC occupation are reconciled before employment weights are applied, so each six-digit occupation's Bureau of Labor Statistics (BLS) employment enters the aggregation only once.

Twenty-one of the 763 unique six-digit SOC occupations lack a positive May 2021 BLS employment weight. These occupations are excluded from the employment-weighted mean within their ISCO-08 group. No ISCO group is left without at least one positively weighted constituent SOC occupation.

Normalization and Component Construction

For O*NET element k and detailed O*NET-SOC occupation j, the normalized value is

$$z_{jk} = \frac{x_{jk} - \min_j(x_{jk})}{\max_j(x_{jk}) - \min_j(x_{jk})},$$

where x_{jk} is the original O*NET value.

The physical-execution composite is

$$P_j = \frac{1}{7}\sum_{k \in \mathcal{P}} z_{jk},$$

where $\mathcal{P}$ contains the seven physical-execution elements.

The live-care-and-teaching composite is

$$L_j = \frac{1}{5}\sum_{k \in \mathcal{L}} z_{jk},$$

where $\mathcal{L}$ contains the five live-care-and-teaching elements.

All 12 constituent elements have complete values in the implemented O*NET sample. Each element uses either the O*NET Importance or Context scale, both ranging from 1 to 5, with higher values corresponding to more of the relevant construct. None of the elements are reverse-coded.

Table A4 reports the O*NET elements, source scales, normalization procedures, activation thresholds, and element weights used in the two implemented human necessity dimensions.

Table A4. O*NET Inputs and Activation Rules

Dimension and activation threshold	O*NET element	Element code	Source scale	Normalization	Element weight
Physical execution, $P_j \geq 0.52$	Performing general physical activities	4.A.3.a.1	Importance (IM), 1–5; higher = more important use of whole-body physical activity	Min-max	1/7
	Handling and moving objects	4.A.3.a.2	Importance (IM), 1–5; higher = more important hands/arms object handling	Min-max	1/7
	Operating vehicles, mechanized devices, or equipment	4.A.3.a.4	Importance (IM), 1–5; higher = more important vehicle/equipment operation	Min-max	1/7
	Physical proximity	4.C.2.a.3	Context (CX), 1–5; higher = closer physical proximity to others	Min-max	1/7
	Time spent standing	4.C.2.d.1.b	Context (CX), 1–5; higher = more time spent standing	Min-max	1/7
	Time spent using hands	4.C.2.d.1.g	Context (CX), 1–5; higher = more time using hands	Min-max	1/7
	Time spent walking and running	4.C.2.d.1.d	Context (CX), 1–5; higher = more time walking or running	Min-max	1/7
Live care and teaching, $L_j \geq 0.64$	Assisting and caring for others	4.A.4.a.5	Importance (IM), 1–5; higher = more important personal, medical, or emotional caregiving	Min-max	1/5
	Training and teaching others	4.A.4.b.3	Importance (IM), 1–5; higher = more important training or teaching role	Min-max	1/5
	Performing for or working directly with the public	4.A.4.a.8	Importance (IM), 1–5; higher = more important direct public-facing service	Min-max	1/5
	Responsibility for others' health and safety	4.C.1.c.1	Context (CX), 1–5; higher = greater responsibility for others' health and safety	Min-max	1/5
	Contact with others	4.C.1.a.4	Context (CX), 1–5; higher = more contact with others	Min-max	1/5

The physical-execution indicator is activated when $P_j \geq 0.52$, and the live-care-and-teaching indicator when $L_j \geq 0.64$.

The activation thresholds were selected during development of the rule-based measure with reference to occupation-level information reported in Richmond (2026a). They were not chosen independently of prior occupational information and were not estimated from Turkish occupational data. Appendix B examines sensitivity to alternative human necessity cutoffs.

Reconciliation to Six-Digit SOC Occupations and SOC-Level Scoring

O*NET includes detailed variants within some six-digit SOC occupations. BLS employment weights correspond to six-digit SOC occupations rather than individual detailed O*NET variants; the detailed records are reconciled before the tier rule and employment weights are applied.

Let $d \in j$ index the detailed O*NET variants associated with six-digit SOC occupation j, and let D_j denote the number of variants. The reconciled physical-execution and live-care-and-teaching composites are

$$P_j^{SOC} = \frac{1}{D_j} \sum_{d \in j} P_{jd},$$

and

$$L_j^{SOC} = \frac{1}{D_j} \sum_{d \in j} L_{jd}.$$

The human necessity tier is then assigned once at the six-digit SOC level:

$$H_j^{SOC} = \begin{cases} 0.90, & \text{if } P_j^{SOC} \geq 0.52 \text{ or } L_j^{SOC} \geq 0.64, \\ 0.15, & \text{otherwise.} \end{cases}$$

A six-digit SOC occupation meeting either the physical-execution or live-care-and-teaching criterion receives $H = 0.90$; an occupation meeting neither criterion receives $H = 0.15$. These are classificatory scores distinguishing strong physical or relational necessity from its absence, not estimates of the magnitude or probability of continuing human necessity.

Table A5 summarizes the scoring rule.

Table A5. Six-Digit SOC Human Necessity Scoring Rule

Activated indicator or indicators	Assigned H_j^{SOC}	Interpretation
Physical execution or live care and teaching	0.90	Human physical presence or direct live interaction is integral to delivery
Neither	0.15	Neither implemented human necessity condition is identified

The classification threshold places the first tier above the cutoff and the residual tier below it. The tier values were not calibrated to Turkish data or to published numerical benchmarks. They encode whether physical execution or live interaction is treated as binding on continued human participation.

SOC-to-ISCO Crosswalk and Aggregation

Six-digit SOC-level scores are mapped to ISCO-08 two-digit occupation groups using a manual SOC-to-ISCO crosswalk. The crosswalk was constructed by comparing SOC-2010 minor-group definitions and occupation titles with the ISCO-08 classification structure and definitions.

Each six-digit SOC occupation is assigned to exactly one ISCO-08 two-digit group. The mapping first uses the SOC major-group and minor-group structure and then applies occupation-title rules to resolve remaining ambiguity. No SOC occupation is divided across multiple ISCO groups.

Following reconciliation and tier assignment, ISCO-level scores are calculated as

$$H_o = \frac{\sum_{j \in o} E_j \, H_j^{SOC}}{\sum_{j \in o} E_j},$$

where H_j^{SOC} is the reconciled human necessity score for six-digit SOC occupation j, E_j is its national employment, and o denotes an ISCO-08 two-digit occupation group.

Each six-digit SOC employment weight is applied once. Six-digit SOC occupations with zero or missing BLS employment weights are excluded from the employment-weighted mean within their ISCO group. No additional rescaling, smoothing, or transformation is applied after aggregation.

Table A6 summarizes the reconciliation, crosswalk, and aggregation procedure.

Table A6. SOC-to-ISCO Aggregation Procedure

Aggregation element	Implemented procedure
Detailed source records	879 O*NET-SOC records
Unique six-digit SOC occupations	763
Six-digit SOC occupations with multiple detailed variants	64
Reconciliation of detailed variants	Physical-execution and live-care-and-teaching composite scores are averaged across detailed variants sharing the same six-digit SOC code; the tier rule is then applied once to the reconciled six-digit occupation
Crosswalk	Manual six-digit SOC-to-ISCO-08 crosswalk
Crosswalk source documents	SOC-2010 occupation titles and minor-group definitions; ISCO-08 structure, titles, and definitions
Employment weights	May 2021 BLS Occupational Employment and Wage Statistics
ISCO-level value	Employment-weighted mean of reconciled six-digit SOC scores
Treatment of many-to-one mappings	All mapped six-digit SOC occupations are aggregated within the corresponding ISCO group
Treatment of one-to-many mappings	Not applicable; each six-digit SOC occupation is assigned to one ISCO group
Treatment of ambiguous mappings	SOC major-group and minor-group branching, supplemented by occupation-title rules
Treatment of zero or missing BLS weights	21 of the 763 six-digit SOC occupations lack a positive BLS employment weight and are excluded from the employment-weighted mean within their ISCO group; no ISCO group is left without a positively weighted constituent occupation
Application of BLS weights	Each six-digit SOC occupation's BLS employment weight is applied once
Additional transformation after aggregation	None
ISCO groups with values derived from matched SOC occupations	37
ISCO groups requiring structured assignment	2

The full six-digit SOC reconciliation is provided in the supplementary replication file. The corrected procedure avoids applying the same six-digit SOC employment weight separately to multiple detailed O*NET variants.

Intermediate ISCO-level values arise because constituent six-digit SOC occupations may receive different H tiers. The activation thresholds are applied before ISCO aggregation; ISCO-level weighted means are not themselves compared with the physical-execution or live-care-and-teaching activation thresholds.

Structured Assignments for Unmatched ISCO Groups

Two ISCO-08 occupation groups lack matched SOC occupations and receive structured assignments: street and related sales and service workers (ISCO 95) and refuse workers and other elementary workers (ISCO 96).

Both groups involve substantial physical presence, on-site execution, interaction with people or materials, and real-time situational response. Both groups are assigned to the high human necessity tier under the same conceptual rules applied to matched occupations.

Table A7 reports the assignments.

Table A7. Structured Assignments for Unmatched ISCO Groups

ISCO-08 code	Occupation group	Assigned H	Basis for assignment
95	Street and related sales and service workers	0.90	Direct public interaction, physical presence, handling or delivery of goods and services, and real-time situational response
96	Refuse workers and other elementary workers	0.90	Sustained physical execution, handling of materials, changing physical environments, and required on-site presence

These groups account for 1.23 percent of private sector employment. Both assignments exceed the $H = 0.60$ alternative threshold examined in Appendix B and remain classified as high human necessity under that specification.

Interpretation and Limitations

The human necessity measure is deterministic conditional on the selected O*NET elements, normalization procedures, activation thresholds, tier values, reconciliation of detailed O*NET variants, crosswalk, and employment weights. It should be interpreted as a structured occupation-level classification input rather than as a direct observation of job content in Türkiye.

The measure relies on U.S. occupational data and U.S. employment weights, which may not fully reflect task organization or occupational composition in Türkiye. Aggregation to ISCO-08 two-digit groups masks heterogeneity across workers, firms, tasks, sectors, and employment arrangements. The manual crosswalk introduces classification judgment, particularly for occupations with ambiguous or overlapping definitions. The activation thresholds, tier values, and detailed-variant reconciliation rule are substantive classification choices rather than estimated parameters.

The measure may understate human necessity for occupations whose continuing human involvement derives primarily from formal certification or licensure rather than physical execution or live care and teaching, as the licensed-or-certified-judgment channel is excluded from the baseline construction owing to incomplete O*NET coverage. It may also understate forms of

human necessity arising from managerial authority, fiduciary responsibility, informal accountability, or relational trust that are not directly captured by the two implemented channels.

The structured assignments for ISCO 95 and ISCO 96 introduce additional judgment because those groups lack matched SOC occupations. Their assignment to the high human necessity tier is based on the implemented physical-execution and live-interaction criteria rather than direct O*NET observations.

Subject to these limitations, the procedure provides a transparent and reproducible basis for constructing occupation-level human necessity scores and aggregating them to ISCO-08.

Appendix B. Threshold Sensitivity Analysis

The archetype classification depends on cutoffs for artificial intelligence (AI) exposure, demand elasticity, and human necessity. Although the paper's principal contribution lies in incorporating demand elasticity and human necessity, the exposure cutoff determines the employment base to which these additional dimensions are applied. This appendix examines sensitivity to all three. The exposure exercise tests the size of the high-exposure employment base, whereas the elasticity and human necessity exercises test how employment is allocated within that base.

The analysis focuses on three features of the main results: the large Less Change share, the position of Reorganize as the largest high-exposure archetype, and the comparatively small Grow with AI share. Each cutoff is varied separately while the other two are held fixed. The alternative values are illustrative perturbations rather than estimated confidence intervals or probability bounds.

Occupations Near the Classification Thresholds

Table B1 reports the occupations closest to each baseline cutoff and most likely to be reclassified under small changes in the relevant threshold.

Teaching professionals lie almost exactly at the exposure cutoff, with a complementarity-adjusted AI occupational exposure (C-AIOE) value of 4.436 compared with the baseline value of 4.437. Legal, social, and cultural professionals; numerical and material recording clerks; sales workers; and general and keyboard clerks are the occupation groups closest to the human necessity cutoff under the baseline two-channel construction. Food processing, woodworking, garment, and other craft and related trades workers lie exactly at the elasticity cutoff of $\eta = -1.000$. Legal, social, and cultural professionals are also close to that boundary.

These occupations are the most likely to drive changes in aggregate archetype shares when individual cutoffs are varied.

Table B1. Occupations Closest to the Baseline Classification Thresholds

Classification dimension	ISCO-08 code	Occupation group	Estimate	Baseline threshold	Absolute distance	Classification under baseline thresholds
C-AIOE	23	Teaching professionals	4.436	4.437	0.001	Less Change
C-AIOE	91	Cleaners and helpers	4.495	4.437	0.058	Reorganize
C-AIOE	75	Food processing, woodworking, garment, and other craft and related trades workers	4.524	4.437	0.087	Grow with AI
C-AIOE	51	Personal service workers	4.349	4.437	0.088	Less Change
H	26	Legal, social, and cultural professionals	0.520	0.500	0.020	Reorganize
H	43	Numerical and material recording clerks	0.470	0.500	0.030	Automation Risk
H	52	Sales workers	0.570	0.500	0.070	Reorganize
H	41	General and keyboard clerks	0.310	0.500	0.190	Automation Risk
η	75	Food processing, woodworking, garment, and other craft and related trades workers	–1.000	–1.000	0.000	Grow with AI
η	26	Legal, social, and cultural professionals	–0.967	–1.000	0.033	Reorganize
η	35	Information and communications technicians	–1.133	–1.000	0.133	Grow with AI
η	21	Science and engineering professionals	–0.850	–1.000	0.150	Automation Risk

Notes: Occupations are ordered within each classification dimension by absolute distance from the baseline threshold. The table reports the four closest occupations for each dimension. An occupation exactly at the elasticity threshold is classified as Grow with AI because the classification rule is $\eta \leq -1.000$.

Aggregate Sensitivity to Alternative Thresholds

Table B2 reports aggregate employment shares under alternative threshold specifications. The exposure threshold is varied by 5 percent in either direction around the C-AIOE value of 4.437. The elasticity threshold is varied by 0.20 points around $\eta = -1.000$, and the human necessity threshold by 0.10 points around $H = 0.50$. These alternatives provide symmetric, readily interpretable perturbations around the classification cutoffs.

Lowering the exposure threshold to 4.215 moves additional occupations out of Less Change and into the three high-exposure archetypes, reducing the Less Change share from 58.7 to 42.7 percent. Raising the threshold to 4.659 increases the Less Change share to 76.4 percent.

Table B2. Sensitivity of Aggregate Employment Shares to Alternative Classification Thresholds

Threshold varied	Specification	Automation Risk (%)	Reorganize (%)	Grow with AI (%)	Less Change (%)
Baseline	C-AIOE ≥ 4.437; $\eta \leq -1.0$; $H \geq 0.50$	12.3	21.3	7.7	58.7
AI exposure	C-AIOE ≥ 4.215(–5%)	12.9	30.0	14.3	42.7
AI exposure	C-AIOE ≥ 4.659(+5%)	9.3	10.6	3.7	76.4
Demand elasticity	$\eta \leq -0.8$	7.6	7.7	26.1	58.7
Demand elasticity	$\eta \leq -1.2$	12.6	25.3	3.5	58.7
Human necessity	$H \geq 0.40$	8.8	24.8	7.7	58.7
Human necessity	$H \geq 0.60$	24.0	9.6	7.7	58.7
Certification treatment	Certification included; unavailable values set to zero	12.3	21.3	7.7	58.7
Certification treatment	Certification included; unavailable values imputed using SOC minor-group means	11.2	22.4	7.7	58.7

Notes: Each threshold specification varies one cutoff while holding the other two at their baseline values. The alternatives are illustrative one-way perturbations and are not confidence intervals. Shares may not sum to 100 because of rounding. Certification is excluded from the baseline human necessity construction because O*NET coverage of the certification item is incomplete for reasons unrelated to occupational certification requirements. The final two rows report alternative treatments of the certification information as robustness checks.

The exposure threshold primarily affects the size of the high-exposure employment base. Lowering the cutoff from 4.437 to 4.215 increases the combined high-exposure share from 41.3 to 57.3 percent; raising it to 4.659 reduces the share to 23.6 percent. Less Change remains the largest archetype under both alternatives.

Relaxing the elasticity cutoff from $\eta = -1.000$ to $\eta = -0.800$ shifts substantially more high-exposure employment into Grow with AI, increasing its share from 7.7 to 26.1 percent. Under this specification, Grow with AI becomes the largest of the three high-exposure archetypes. Sales workers account for much of this change: their elasticity of $\eta = -0.850$ lies between the baseline and relaxed cutoffs, and they represent 10.6 percent of private sector employment. Tightening the

cutoff to $\eta = -1.200$ reduces the Grow with AI share to 3.5 percent, with most of the reclassified employment moving to Reorganize.

Changing the human necessity cutoff affects the division between Reorganize and Automation Risk among high-exposure occupations with constrained demand. Lowering the cutoff from $H = 0.50$ to $H = 0.40$ reduces the Automation Risk share from 12.3 to 8.8 percent and raises the Reorganize share from 21.3 to 24.8 percent. Raising the cutoff to $H = 0.60$ shifts employment in the opposite direction, increasing Automation Risk to 24.0 percent and reducing Reorganize to 9.6 percent.

Including certification with unavailable values set to zero reproduces the baseline aggregate shares. Imputing unavailable certification values using Standard Occupational Classification (SOC) minor-group means moves administrative and commercial managers (International Standard Classification of Occupations (ISCO) 12) from Automation Risk to Reorganize, reducing the Automation Risk share to 11.2 percent and increasing the Reorganize share to 22.4 percent. Grow with AI and Less Change are unchanged. The imputation is not used in the baseline construction because it introduces an additional modeling assumption and many imputed values lie close to the certification activation threshold.

Results

Less Change is the most robust feature of the classification, remaining the largest archetype under every specification. The allocation of high-exposure employment is more sensitive to the elasticity and human necessity cutoffs. Reorganize is the largest high-exposure archetype under the baseline specification and most illustrated one-way perturbations, but Grow with AI becomes largest when the elasticity cutoff is relaxed to $\eta = -0.800$, and Automation Risk becomes largest when the human necessity cutoff is raised to $H = 0.60$. These results do not imply an invariant ordering of the high-exposure archetypes; rather, they show that the relative shares depend materially on assumptions about demand responsiveness and continuing human necessity.