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Transformation of Routine Jobs in the Türkiye Labor Market: A Quantitative Analysis of the Effects of Artificial Intelligence and Technological Change on Employment (2014–2024)

Abstract

This study quantitatively analyzes the transformation of Türkiye's labor market between 2014 and 2024 in terms of job task intensity. Using Mihaylov and Tijdens' (2019) ISCO-08 task dataset and TurkStat employment data, it identifies major structural shifts driven by technological progress and artificial intelligence–assisted automation. The share of non-routine cognitive jobs increased by 5.2%, while routine manual and non-routine manual jobs declined by 3.3% and 1.8%, respectively. These findings indicate a transition toward knowledge-based sectors and growing employment polarization. High-skilled professional and technical roles expanded, whereas middle-skilled occupations, including skilled agriculture and artisanal work, contracted. Wage structures increasingly favored high-skilled, non-routine cognitive occupations, while gender pay disparities persisted. The study underscores the need for vocational education reforms, targeted incentives, and large-scale reskilling programs to enhance labor market adaptability to technological change.

Keywords: *Routine Jobs, Employment Polarization, Artificial İntelligence, Automation, Türkiye Labor Market*

Rutin İşlerin Türkiye İşgücü Piyasasındaki Dönüşümü: Yapay Zekâ ve Teknolojik Değişimin İstihdam Üzerindeki Etkilerine İlişkin Nicel Bir Analiz (2014–2024)

Öz

Bu çalışma, 2014–2024 döneminde Türkiye işgücü piyasasının iş görevi yoğunluğu açısından geçirdiği dönüşümü nicel olarak incelemektedir. Mihaylov ve Tijdens'in (2019) ISCO-08 görev veri seti ile TÜİK istihdam verileri kullanılarak, teknolojik ilerleme ve yapay zekâ destekli otomasyonun yön verdiği önemli yapısal değişimler belirlenmiştir. Bulgular, rutin olmayan bilişsel işlerin payının %5,2 arttığını; rutin manuel ve rutin olmayan manuel işlerin ise sırasıyla %3,3 ve %1,8 azaldığını göstermektedir. Bu durum, bilgi temelli sektörlere geçişi ve artan istihdam kutuplaşmasını ortaya koymaktadır. Yüksek vasıflı mesleki ve teknik roller genişlerken, orta vasıflı tarım ve zanaatkârlık alanları daralmıştır. Ücret yapıları, rutin olmayan bilişsel işlerde yoğunlaşan yüksek vasıflı grupları lehine şekillenmiş; cinsiyete dayalı ücret eşitsizliği ise sürmüştür. Çalışma, mesleki eğitim reformları, *hedefli teşvikler ve kapsamlı yeniden beceri kazandırma programlarının işgücü piyasasının teknolojik değişime uyumunu güçlendireceğini vurgulamaktadır.*

Anahtar Kelimeler: *Rutin İşler, İstihdam Kutuplaşması, Yapay Zekâ, Otomasyon, Türkiye İşgücü Piyasası*

Introduction

In the period following the Second World War, Europe experienced rapid economic growth and full employment, dominated by the manufacturing sector. Most employees were employed in full-time and permanent jobs. However, from the 1970s onwards, with the impact of globalization, European economies underwent a radical transformation, and the manufacturing sector was gradually replaced by the service sector, which led to the shrinkage of middle-skilled, middle-wage occupational groups in industrialized countries and initiated a process of "deindustrialization" (Macias, Hurley, & Rafferty, 2015).

During the same period, in developing countries such as Türkiye, the share of routine jobs initially increased owing to the impact of globalization and industrialization. However, the spread of computerization in the 2000s led to a decline in the share of routine manual jobs (Aedo, Hentschel, Moreno, & Luque, 2013). This structural transformation has had significant effects on the labor market, such as a decline in jobs requiring middle-level skills, changes in wage distribution, and a transformation in sectoral composition.

In recent years, debates have intensified regarding how new technological developments will shape the future of work and which occupations will disappear and which will come to the fore. In this context, researchers such as Frey and Osborne (2017), David and Dorn (2013), Autor and Dorn (2009), and Acemoglu and Autor (2011) have conducted studies to determine which jobs are at risk of extinction by examining the effects of automation and digitalization on employment.

The extent to which an occupation is affected by automation depends on the nature of the tasks involved. Therefore, categorizing occupations based on routine/non-routine and manual/cognitive tasks is instructive in identifying those at a high risk of being replaced by machines. This analysis can help us predict which occupational groups will be at greater risk in the labor market in the future due to automation.

Workers in developed countries are undertaking fewer routine tasks, and their labor force profile is gradually shifting towards non-routine cognitive work. In contrast, in relatively less developed countries, the share of routine jobs in employment is higher (Lewandowski, Park, Hardy, & Du, 2019). This is explained by the shift in routine and labor-intensive jobs from developed economies to countries with low labor costs as a result of globalization. This shift increases employment opportunities in underdeveloped and developing countries where jobs are relocated. However, this process also intensifies competition on a global scale and exerts downward pressure on wages, especially in routine manual jobs. As a matter of fact, with the wave of globalization in the post-1980 period, while the share of routine-intensive jobs has significantly decreased in developed countries, this trend has been in the opposite direction in relatively less developed countries.

Since jobs in the manufacturing sector are generally small and routine in nature, they can be easily performed by personnel with lower levels of education and qualifications, which offers multinational companies the opportunity to gain cost advantages. It encourages them to shift routine-intensive jobs to underdeveloped and developing countries where low wages prevail. The high unemployment rates in these countries, the large young population, and the relatively low average level of education increase the demand for routine jobs. However, although this situation creates employment opportunities in the short term, in the medium and long term, with the spread of automation and mechanization, it brings with it the risk of loss of employment in the same business areas.

Today, technology is no longer just a threat to automate routine tasks but has taken on the role of an assistant for highly trained office workers, complementing and empowering their work. However, the continuous advancement of technology and developments in artificial intelligence have begun to enable the automation of even non-routine cognitive tasks that were once considered safe for human workers. Indeed, the rise of artificial intelligence will directly affect many professions and tasks that have been relatively unaffected by automation (Tolan et al., 2021). In this new wave, non-routine manual jobs where artificial intelligence is still limited in interaction with the physical world, such as the service sector, seem relatively sheltered, but wage pressure continues even in this field.

Some occupational groups operating in the service sector cannot be relocated because of the simultaneity and geographical constancy of production and consumption processes. In the service sector (such as restaurant and personal care services), many activities are fundamentally location-dependent and therefore cannot be relocated abroad. Moreover, the substitution of these jobs through automation is limited by both technological constraints and consumer preferences for human interaction. These conditions pave the way for an increasing number of relatively low-skilled and low-paid employment opportunities in these industries.

The main objective of this study is to quantify the relative share of routine and non-routine jobs in the Turkish labor market and examine the possible effects of changes in this structural composition on employment. Understanding the level of job routineness in an economy and its change over time is critical for assessing the effects of mechanization and automation on the employment structure. Accordingly, to measure the level of routineness of occupations in

Türkiye, the dataset in Mihaylov and Tijdens (2019), *Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations*, is applied to the Turkish labor market. Thanks to this application, occupation-specific routine and non-routine task content can be analyzed in detail in the Turkish context.

The research aims to address the risk of polarization that these trends pose for the Turkish economy and their potential impact on income inequality. Ultimately, in light of the findings, it is planned to develop adaptive strategies for policymakers, educational institutions, and social partners and to present a set of policy recommendations that will compensate for the disruptive effects of artificial intelligence while simultaneously maximizing its complementary potential.

Within the scope of this study, answers to the following research questions regarding the Turkish labor market are sought:

*What is the distribution of routine, non-routine, cognitive, and manual tasks in the Turkish labor market?

*How has the share of routine/non-routine and cognitive/manual tasks changed during the 2014–2024 period?

*What is the trend of employment polarization in the Turkish labor market during this period?

*What is the general outlook of wage distribution by occupational groups in Türkiye?

Literature Review

Although there is literature on analyzing occupational task content (routine, non-routine, manual, and cognitive), there is a fundamental problem limiting the production of internationally comparable data. The use of different occupational classification systems across countries and the heterogeneous nature of labor markets are the main obstacles to establishing a standard measurement method. Despite these methodological difficulties, various studies have aimed to quantitatively monitor this transformation and enable cross-country comparisons.

Autor and Dorn (2009) developed a “routine intensity index” to measure the routine task content of occupations. Their findings on the U.S. labor market reveal a significant decline in the share of jobs with high routine task intensity. In contrast, employment in two different categories of non-routine jobs increased. The first is high-skilled jobs that require advanced skills such as problem solving, abstract reasoning, and decision-making. The second is service-oriented occupations that require basic interpersonal communication but with low levels of education and skills.

Acemoglu and Autor (2011) developed a comprehensive methodology to analyze the task content of occupations using the Occupational Information Network (O*NET) database. This methodology aims to establish standard indices for non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine cognitive, and routine manual job tasks. The findings of the study reveal broad-based employment growth in high- and low-skilled occupations while simultaneously finding that capital is replacing labor in routine tasks performed by middle-skilled workers due to technological advances.

Frey and Osborne (2017) developed a methodology to measure the sensitivity of occupations to automation and computerization by analyzing 702 occupations in detail. In light of the estimates obtained from this methodological framework, the researchers aimed to examine its possible effects on the U.S. labor market. Accordingly, this study presents the high-risk employment rate and the estimated probability of computerization of occupations.

Autor and Dorn (2013) analyzed occupations in three main categories according to their task content: manual, routine, and abstract cognitive tasks. Routine tasks are divided into routine cognitive and manual tasks. An empirical study covering 722 transport regions in the U.S. revealed that low-skilled workers are shifting from routine-intensive jobs to the service sector. As a result of this structural transformation, the study finds that wage distribution is polarized and that the rate of adoption of information technologies has increased.

Autor, Levy, and Murnane (2003) distinguished between cognitive and manual tasks, and routine and non-routine tasks. They stated that computerization would reduce labor input in routine manual and routine cognitive tasks and increase labor input in non-routine cognitive tasks. They also argued that the increase in non-routine tasks will expand the labor force due to the complexity of these tasks and that computerization will complement employees and increase productivity.

Lewandowski, Park, Hardy, and Du (2019) developed a measurement method using various datasets from 41 countries to analyze the global distribution of routine and non-routine work. The study draws on sources such as the OECD's PIAAC program, the World Bank's STEP surveys, and the Chinese Urban Labour Force Surveys (CULS). Cross-country comparisons revealed that as a country's Gross Domestic Product (GDP) increases, the routine task intensity in high-skilled jobs tends to decrease. Moreover, the researchers found that globalization has a differential impact on routine-intensive work. While this process increases routine-intensive employment in low-income countries, it plays a decreasing role in high-income countries.

Mihaylov and Tijdens (2019) created a comprehensive dataset using 3,264 occupation-specific task sets to analyze 437 occupational groups according to the ISCO-08 four-digit classification. This dataset consists of five basic measures: non-routine analytical, non-routine interactive, routine cognitive, routine manual, and non-routine manual. Each occupation can be assigned to one or more of these five groups. The groups in which occupations are included depend on two basic criteria: the level of substitutability with technology and whether task performance requires predominantly manual or cognitive skills.

Classification of Professions According to Task Content

Tasks in occupations are classified into four main categories: routine manual, routine cognitive, non-routine manual, and non-routine cognitive. In the literature, non-routine cognitive tasks are divided into two subclasses: routine analytical and routine interactional (Jaimovich & Siu, 2012; Mihaylov & Tijdens, 2019; Lewandowski et al., 2019).

A task is defined as “routine” if it can be performed by machines operating according to pre-programmed rules. Operations such as monitoring the temperature on a steel melting line or placing glass in a fixed position on an assembly line are examples of manual routine tasks. Because these tasks are based on the continuous repetition of an unchanging procedure, they can be easily performed by automation systems (Autor, Levy, & Murnane, 2003). Routine tasks are generally analyzed in two main categories: routine manual and routine cognitive. Routine manual tasks include occupations based on physical repetition, such as manufacturing, transport, material handling, maintenance, and repair. Routine cognitive tasks, on the other hand, include tasks based on the repetition of prescribed mental processes, which are mostly seen in office and administrative support jobs and certain sales occupations (Jaimovich & Siu, 2012).

Non-routine tasks, on the other hand, are defined as tasks for which the rules required to be transferred to computer code and implemented by machines are insufficiently defined. For example, driving a car in city traffic is classified as a non-routine task because it requires dynamic and unpredictable conditions (Autor et al., 2003). It is stated that such tasks are difficult to automate with existing technology because the procedures to be followed cannot be clearly formulated and require complex skill sets (Acemoglu & Autor, 2011). Non-routine tasks can generally be analyzed in two main categories: cognitive and manual. These two categories exhibit different profiles in terms of occupational distribution.

Non-routine cognitive tasks require advanced mental skills, such as problem solving, intuition, and persuasion. Those working in this field usually have a high level of education and advanced analytical skills. Non-routine manual tasks rely on environmental adaptation, interpersonal communication, and face-to-face interaction skills. Janitorial, cleaning, child and patient care, construction labor, security, and motor vehicle operators can be considered in this context. These occupations require strong communication and physical skills and generally remain at a low level in terms of formal education requirements (Autor, 2010).

Occupations can be classified into four main categories based on their task content. Non-routine cognitive occupations consist of senior managers, such as doctors, financial analysts, computer programmers, economists, professional occupations, and technical personnel. Routine cognitive occupations include office and administrative jobs, such as secretaries, bank tellers, sales clerks, postal clerks, and data entry clerks. Routine manual occupations include blue-collar occupations such as machine operators, tailors, and manufacturing and assembly workers. On the other hand, non-routine manual occupations include jobs concentrated in the service sector, such as janitors, gardeners, and home and personal care workers (Jaimovich & Siu, 2012). Non-routine manual tasks are usually performed by low-skilled workers. Agricultural laborers, mining and construction workers, and drivers can be considered in this category. Given the current technological level, the possibility of machine substitution for labor in these occupations is limited (Keister & Lewandowski, 2017).

Table 1: Distribution of Routine and Non-Routine Tasks among Occupational Groups (Adapted from David and Dorn (2013) and Acemoglu and Autor (2011).

	Cognitive	**Manuel**
Routine	➢ Clerical support workers ➢ Service and sales workers	➢ Craftsmen and Related Occupations ➢ Plant and machine operators and assemblers ➢ Elementary occupations
Non-Routine	➢ Managers ➢ Professionals ➢ Technicians and associate professionals	➢ Service and sales workers ➢ Skilled agricultural, forestry and fishery workers

The automation of routine occupations requires the presence of certain skilled occupational groups to design and manage the process. Highly skilled workers, such as managers, professionals, technicians, and assistant professionals, are among these groups. These professions, which increase productivity by improving automation processes, also contribute to raising employment and wage levels in their respective fields. However, this situation has led to polarization in the labor market. While employment increases in these skilled occupational groups, employment in routine occupations such as artisans, machine operators, assemblers, and workers in jobs that do not require qualifications shrinks due to automation.

Transformation of Routine Work in the Age of Artificial Intelligence

The literature suggests that the impact of automation on the labor market will be more pronounced in routine-intensive occupations with well-defined procedures that can be easily substituted by complex algorithms (Frey & Osborne, 2017). This is supported by a concrete trend in the U.S. economy. Since the 1970s, labor demand for routine cognitive and manual tasks has declined, whereas labor input for non-routine analytical and interactional tasks has steadily increased. This structural transformation has been particularly intense in rapidly digitizing sectors. While automation trends were limited before the 1960s, a significant acceleration and expansion have been observed since then (Autor, Levy, & Murnane, 2003). Computers and automation systems demonstrate high efficiency in routine and well-defined tasks. However, despite advances in artificial intelligence, workforce replacement remains limited in some areas. Notably, automating professional occupations and managerial positions that require complex cognitive skills is particularly challenging. Non-routine cognitive tasks involve human-specific abilities such as flexibility, creativity, problem solving, and complex communication; therefore, computers have a limited capacity to replace humans in these areas (Bresnahan, Brynjolfsson, & Hitt, 2002). However, recent advances in computer technology have begun to address these limitations. For example, the transformation of manual tasks in the transportation and logistics sectors by autonomous driving technologies is clear evidence of this transition (Frey & Osborne, 2017). Artificial intelligence stands out with its tendency to automate routine tasks and, with this feature, has the potential to substitute humans in non-routine cognitive as well as physical tasks. While this process leads to the displacement of existing tasks through automation, it is anticipated that it may increase the demand for humans in new task areas in the future. However, AI is expected to intensify the effects of automation, leading to negative consequences such as polarization in employment, stagnant wage growth, and increasing inequality. Although there is concern that productivity gains will not be shared fairly across society, it is thought that these effects can be mitigated with appropriate policy interventions (Tyson & Zysman, 2022). Artificial intelligence affects the labor market as both a transformative and substitutive force. While significantly increasing productivity through automation in routine cognitive (data entry) and manual (assembly line) tasks, it poses a risk of displacement for jobs that perform these tasks. In contrast, AI also plays a complementary role. By enhancing human skills, productivity in non-routine tasks that require complex problem solving, creativity, and strategic thinking is increased. While this process creates new professions, such as data scientists, it necessitates skill renewal and lifelong learning for the existing labor force to adapt to this change (Santhosh, Unnikrishnan, Shibu, Meenakshi, & Joseph, 2023).

The adoption of artificial intelligence in the business world deeply affects employees' existing skills and obliges them to a continuous process of learning, skill development, and reskilling to adapt to this technological transformation (Cramarenco, Burcă-Voicu, & Dabija, 2023). As a matter of fact, five basic skills that employees in multinational companies need to develop in order to adapt to a working environment compatible with artificial intelligence have been identified. These skills include data analytics and literacy, proficiency in the use of digital tools, complex cognitive skills, data-supported decision-making, and effective continuous learning capacity (Jaiswal, Arun, & Varma, 2023).

Productive AI appears to play a complementary role in routine cognitive tasks, such as typing, resulting in significant productivity gains. For example, one study found that using ChatGPT reduced writing time by 40% and improved text quality by 18%. Such applications can make positive contributions to non-routine cognitive tasks by both increasing productivity and reducing productivity inequality (Noy & Zhang, 2023). However, the same technological progress may lead to negative consequences, such as polarization in employment, a slowdown in wage increases, and deepening income inequality. Despite concerns that productivity gains will not be distributed fairly across all segments of society, these risks can be controlled with the right policy interventions (Tyson & Zysman, 2022).

Method

In this study, the dataset developed by Mihaylov and Tijdens (2019), which covers 427 four-digit ISCO-08 occupational groups, is used as the basis for the classification of occupations based on task intensity. The dataset evaluates occupations in five different categories: Non-Routine Analytical, Non-Routine Interactive, Routine Cognitive, Routine Manual and Non-Routine Manual. In the present analysis, the Non-Routine Analytical and Non-Routine Interactive categories were combined under the main heading of 'Non-Routine Cognitive' to ensure methodological integrity. Quantitative data on employment were obtained from the Turkish Statistical Institute (TurkStat) databases, and for the final analyses, proportional distributions based on occupational groups were calculated and prepared for analysis.

The main reasons for using this dataset in this study are that the occupational classification in Türkiye is compatible with the ISCO system, the dataset does not limit occupations to a single task intensity but considers different task types, and it is one of the most recent datasets in the field. In this study, non-routine analytical and non-routine interactive tasks were combined and evaluated under the "non-routine cognitive" category. As the TurkStat database does not share the subdivisions of occupations, occupational task intensities were distributed proportionally according to their weights within the relevant occupational groups. To make more accurate measurements, there is a need to develop a methodology specific to the Turkish labor market and access detailed subdivisions of occupations. Although the data obtained are limited in representing the task intensities of jobs in Türkiye, they are important for identifying changes over the years and conducting a general trend analysis.

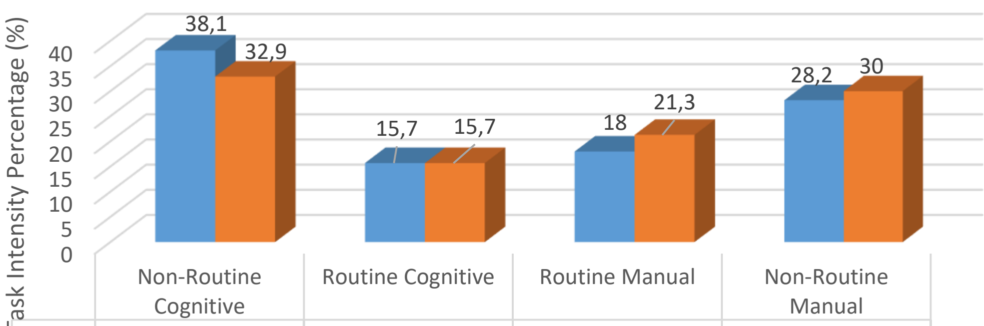
Findings

This study aims to reveal the structural transformation that has taken place in the Turkish labor market between 2014 and 2024, based on the task intensity of occupations. Within the scope of this research, occupations were classified according to their routine and non-routine task intensity, and the effects of this classification on employment polarization and wages were examined.

The Transformation of Routine Occupations in the Turkish Labor Market

To monitor the structural transformation of the economy and the extent to which it is affected by technological change, the current state of routine jobs serves as a critical indicator. These jobs are of great importance because of their vulnerability to automation and their representation of the middle-skilled employment base. In emerging economies, changes in routine jobs allow us to understand structural indicators ranging from the pace of technological adaptation to skill transitions and income distribution. Therefore, monitoring the share of routine jobs in the labor market not only tracks occupational transformation but also reveals the deep transformation of the labor market. Figure 1 shows the change in the ratio of routine/non-routine and manual/cognitive employment over the years.

Figure 1: Change in the Distribution of Task Intensity of Jobs in Türkiye Over the Years (2014-2024)



	Non-Routine Cognitive	Routine Cognitive	Routine Manual	Non-Routine Manual
2024	38,1	15,7	18	28,2
2014	32,9	15,7	21,3	30

Structural Transformation of Türkiye's Labor Market

Data reflecting the structural transformation of Türkiye's labor market between 2014 and 2024 reveal the significant impact of technological change and automation on the distribution of occupational tasks. Over the approximately ten-year period, the share of non-routine cognitive tasks increased significantly from 32.9% to 38.1%, strongly indicating that the economy is evolving towards knowledge-based production processes. Studies show a strong positive correlation between economic development and non-routine cognitive jobs, and a clear negative correlation between economic development and the intensity of manual skill use (both routine and non-routine) (Aedo, Hentschel, Moreno, & Luque, 2013).

Improvements in the quality and cost reductions of computer and communication technologies have enabled routine tasks to be increasingly performed by software and machines. Alternatively, the same tasks can be relocated to countries with relatively low-wage labor (Autor, 2010). However, the current level of sophistication of these technologies makes it increasingly difficult for low-cost human labor to compete with machines in routine tasks. Furthermore, the increase in the share of non-routine cognitive work points to a growing need for skilled human abilities, such as creativity, problem solving, adaptability, and complex communication.

During the period in question, the share of routine manual jobs decreased by 3.3%, from 21.3% to 18%. Similarly, non-routine manual jobs decreased by 1.8%, from 30% to 28.2%. The decline in manual occupations indicates that such jobs have either disappeared or become significantly less dependent on human labor owing to the widespread use of robotic systems and smart machines in the manufacturing and production sectors. The share of the agricultural sector in Türkiye's total employment is still higher than that in developed countries. Mechanization in the agricultural sector and migration to cities have led to a decline in agricultural employment. The decline in the agricultural sector is also thought to have led to a decline in the share of non-routine manual jobs.

These findings are consistent with the occupational transformation trends identified by Acemoglu and Autor (2011) for Central and Eastern Europe. In this context, they examined changes in the occupational structure of 10 Central and Eastern European countries between 1998 and 2013. They found that in all countries examined, the intensity of manual tasks (both routine and non-routine) decreased, while the intensity of non-routine cognitive tasks increased. This indicates that the technological transformation at the global level has produced similar results in Türkiye.

The proportion of routine cognitive tasks in the occupations of office and customer service workers and sales personnel is 15.7%. There has been no change in the proportion of routine cognitive tasks between 2014 and 2024. With the spread of computerization, demand for office and information-processing occupations involving routine cognitive tasks has increased. In the nineteenth century, the introduction of typewriters led to a very significant increase in demand for the clerical profession. However, unlike that period, current technological developments allow for the direct automation of such tasks, and therefore, the increase in demand for similar occupations has been more limited (Autor, Levy, & Murnane, 2003).

In the office and customer service sectors, with traditional office tasks falling prey to automation, the remaining administrative work has increasingly centered around less routine tasks. To illustrate this transformation, the U.S. Department of Labor's *Occupational Handbook* classifies the secretarial profession as encompassing routine tasks such as correspondence and managing telephone traffic. However, with technological advances and the evolution of organizational structures, the roles of secretaries have changed significantly. Increasing office automation and restructuring processes have led secretaries to take on more complex responsibilities that were previously performed by managers and professional staff (Autor et al., 2003).

The banking sector is a good example of how computerization has eroded routine cognitive tasks. With the proliferation of personal computers, many banking transactions can now be performed directly by customers. Despite the increase in transaction volumes, this has not led to a proportional increase in the number of bank employees in the sector. However, the automation of low-skilled routine tasks is only possible because of highly qualified and educated employees in non-routine cognitive occupations. This skilled workforce increases efficiency and profitability by enabling robots to perform routine tasks while driving professional transformation.

The level of development of a country significantly affects the distribution of task intensity in labor markets. In relatively more developed economies, the share of non-routine cognitive tasks is higher, and more advanced education and qualifications are required in these areas, while the share of routine tasks generally remains at lower levels. This finding is also supported by the study conducted by Lewandowski, Park, Hardy, and Du (2019). The study found that the intensity of routine tasks in certain occupations varies by country. For example, workers in high-skill occupations in developed countries perform fewer routine tasks than workers in similar occupational groups. Similarly, routine tasks were found to be less intensive in developed countries for occupational groups such as service and sales workers and craftsmen. In contrast, the relationship between a country's level of development and the intensity of routine tasks is more variable in groups such as plant and machine operators, assembly workers, office and customer service workers, and those in unskilled jobs. Overall, the results of this study show that in countries with a high GDP per capita, the share of non-routine tasks in highly skilled occupations is also higher. In the context of Türkiye, the share of manual tasks (routine and non-routine) is decreasing, whereas the share of non-routine cognitive tasks is increasing.

Polarization of Employment

There is strong evidence that technological progress has led to polarization in the labor market by reducing the employment of medium-skilled workers, particularly those engaged in routine labor-intensive jobs (Keister & Lewandowski, 2017). While employment in medium-skilled and medium-wage jobs is shrinking, employment in high- and low-skilled jobs, which are more resistant to automation, is increasing (Autor, Levy, & Murnane, 2003). This trend is causing the employment structure to shift from the middle to the extremes, leading to the emergence of the phenomenon of employment polarization. Table 2 shows the change in the share of employment by occupational group over the years.

Table 2: Share of Occupational Groups in Employment by Year (%)
(TurkStat, Education Distribution by Occupational Groups data was created using the ILO (2013) Global Employment Trends For Youth (p.29) study).

Educational Level Required	Occupational Groups	2014	2024
Higher Education	1 - Managers	5,2%	5,6%
	2 - Professionals	9,2%	12,5%
	3 - Technicians and associate professionals	5,4%	7,0%
Secondary education	4 - Clerical support workers	6,7%	7,0%
	5 - Service and sales workers	18,3%	19,6%
	6 - Skilled agricultural, forestry and fishery workers	16,7%	11,1%
	7 - Craft and related trades workers	14,2%	13,2%
	8 - Plant and machine operators and assemblers	9,3%	9,6%

Primary education	9 - Elementary occupations	15,1%	14,4%
	Total	100,0%	100,0%

Employment Polarization in Türkiye

Table 2 reflects the transformation of Türkiye's employment structure between 2014 and 2015, indicating polarization trends in employment. The polarization hypothesis suggests that, owing to technological change and the structural effects of the global economy, the share of occupations requiring medium-level skills is declining, while the weight of high- and low-skill jobs in total employment is increasing (Alabdulkareem, Frank, Sun, AlShebli, Hidalgo, & Rahwan, 2018).

Significant increases were observed in the “Professionals” and “Technicians and Associate Professionals” categories in the higher education group, rising from 9.2% to 12.5% and from 5.4% to 7.0%, respectively. This is consistent with employment expansion in knowledge-intensive sectors and indicates an increase in demand for highly skilled labor. On the other hand, within secondary education-level occupational groups, the employment shares of “Skilled Agriculture, Forestry, and Fisheries” and “Artisans and Related Workers” decreased from 16.7% to 11.1% and from 14.2% to 13.2%, respectively. These declines indicate that traditional medium-skilled employment areas are shrinking.

However, the increase in the share of “Service and Sales Workers” from 18.3% to 19.6% in the same education group shows that employment is shifting toward the low- to medium-skilled service sector. The slight decrease in unskilled jobs (from 15.1% to 14.4%) shows that employment losses in sectors such as agriculture have not been entirely transferred to low-skilled job sectors. This indicates that the real transformation in employment is shifting toward high-skilled and service-oriented low- to medium-skilled jobs rather than medium-skilled jobs.

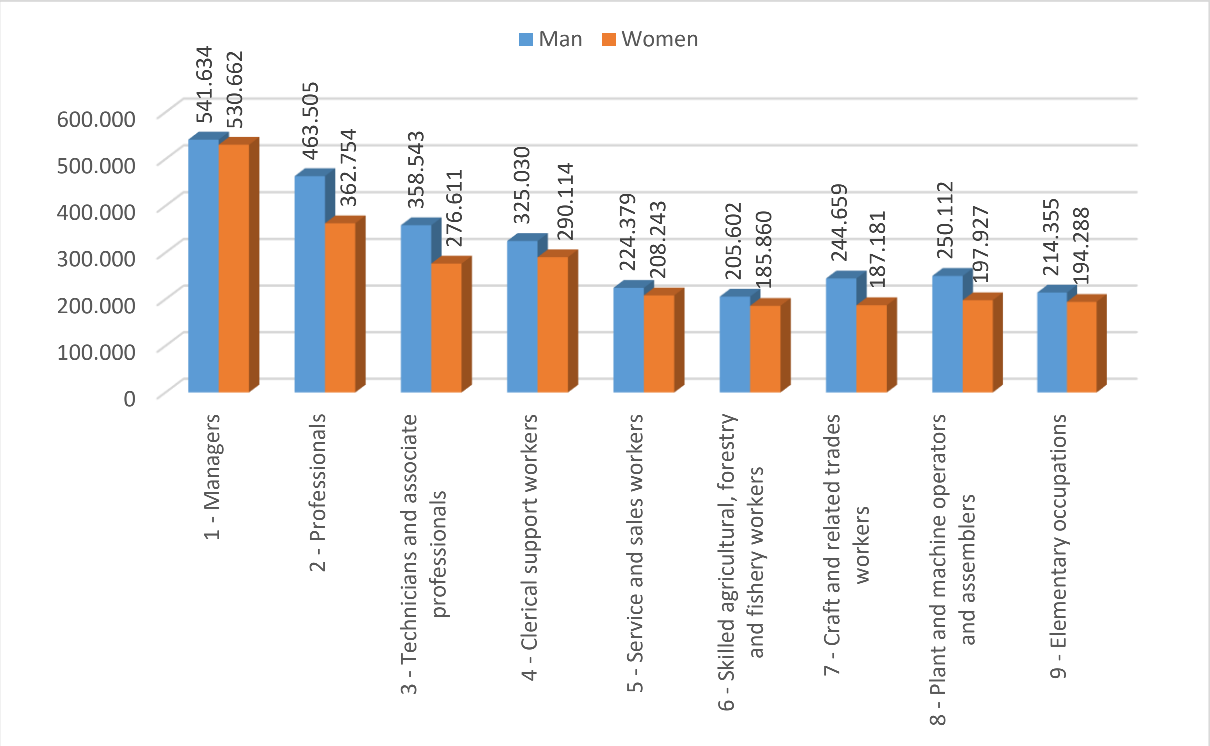
The Turkish labor market appears to be undergoing a structural transformation that works against traditional occupations requiring medium-level skills. This trend aligns with a model that can be described as employment polarization. It points to a dual structure in which high-skilled and low-skilled service jobs are gaining prominence in the economy, while agricultural and manual labor–intensive production jobs are declining.

Service occupations such as hairdressing and waitressing require intensive face-to-face communication. Occupations such as cleaning and security, however, are relatively resistant to robotization because they require direct access to physical environments. Meanwhile, advances in computer technology and falling prices for technological products have driven down wages for routine tasks and increased unemployment in these areas. This situation has directed low-skilled labor toward the service sector, which is difficult to automate. The low skill requirements of this sector and its reliance on physical proximity and interpersonal interaction are among the main factors that make automation difficult (David & Dorn, 2013).

Wage Distribution

In most developed countries, wage distribution shows a clear differentiation based on the nature of work. Manual jobs are paid the lowest wages, non-routine jobs are paid the highest wages, and routine cognitive jobs are generally rewarded with medium-level wages (Goos, Manning, & Salomons, 2014). This situation is also observed in Central and Eastern European countries. It has been found that the workforce in the highest wage bracket performs non-routine cognitive tasks, while those in the lower wage groups are predominantly concentrated in manual jobs (Keister & Lewandowski, 2017). Simultaneously, the literature emphasizes that routine-intensive tasks are largely performed by medium-skilled and medium-wage workers (Acemoglu & Autor, 2011). In light of these findings, it can be concluded that medium-wage jobs predominantly consist of routine tasks.

Figure 2: Annual Average Gross Earnings (TL) by Occupational Group, 2023
(Created by the author based on Income Structure Statistics from TurkStat (2023).



According to TurkStat's (2023) income structure studies, occupational groups with a high proportion of non-routine cognitive tasks rank the highest in terms of wages. In this context, managers, professionals, technicians, technologists, and associate professionals constitute the top three occupational categories with the highest wage levels.

Routine manual tasks performed by medium- and low-skilled workers are becoming increasingly susceptible to automation due to technological advances. These routine manual tasks are concentrated primarily in the occupational groups of “plant and machine operators and assemblers” and “craftsmen and related workers” (Keister & Lewandowski, 2017). Similarly, Mihaylov and Tijdens (2019) identified the top three occupational groups with the highest concentration of routine manual tasks as “craftsmen and related workers,” “plant and machine operators and assemblers,” and “skilled agricultural, forestry, and fishery workers,” respectively. As shown in Table 2, based on TurkStat data, the share of these three occupational groups in total employment in Türkiye decreased from 40.2% in 2014 to 33.9% in 2024. The decline in employment in these occupations—located in the middle range of the wage distribution—combined with the impact of automation, has led to wages becoming increasingly concentrated at the upper and lower ends of the spectrum, thereby deepening polarization in the labor market.

Türkiye’s young population structure and its large female population with high labor force participation potential carry the risk of increasing unemployment rates. Studies indicate that workers in routine, labor-intensive jobs are largely young people (aged 15–24) and women (Lewandowski et al., 2019). It is therefore foreseeable that a contraction in such jobs could push these groups toward the service sector, which generally requires lower skills. Such a shift could lead to further wage suppression due to increased labor supply in the service sector. Women’s lower wages across all occupational groups, combined with their traditionally assigned caregiving roles, structurally limit their career advancement and highlight gender-based wage inequality across all occupational levels.

The literature contains numerous studies emphasizing the disruptive effects of technological developments on income distribution. For example, Davis (1998) argues that technological change is one of the main causes of wage inequality in the United States. In this process, the changing relative demand for skilled and unskilled labor has widened the wage gap between the two groups. A similar dynamic applies in Türkiye. The increasing share of non-routine cognitive tasks in employment, coupled with the declining share of routine manual tasks, has deepened wage differences between occupational groups and contributed to the deterioration of income distribution.

Conclusion

In the early stages of industrialization, routine manual tasks that employed unskilled workers gained prominence as tasks were simplified. However, with technological advancements, these routine, labor-intensive tasks are increasingly being replaced by automation and computerization. As a result of this process, significant job losses have occurred in occupations with a high proportion of routine tasks, such as manufacturing. While these losses are particularly noticeable in the manufacturing sector, most of the labor force displaced from this sector finds employment opportunities in the service sector, which generally offers lower wages. This transformation, brought about by automation, has profoundly affected the occupational composition of the labor market. Indeed, today, the share of routine manual tasks in total employment has decreased significantly, whereas the share of non-routine cognitive tasks has increased.

In Türkiye, in line with the global trend of digital transformation, the demand for non-routine cognitive occupations performed by highly skilled workers is steadily increasing. This trend is evident in employment data from the past decade. During this period, the highest growth rate in total employment was 3.3% in the professional occupation group. This was followed by a 1.6% increase in the technician, technologist, and associate professional occupation groups. Both groups require high qualifications and education levels. During the same period, the proportion of managers in total employment increased by 0.4%.

The employment structure is becoming increasingly polarized owing to technological transformation. At one end of this polarization are highly skilled and well-paid cognitive occupations, while at the other end are low-paid service sector jobs that require less skill. Meanwhile, routine manual occupations, which form the backbone of the traditional middle class, are disappearing rapidly. Those who become unemployed in these occupations often turn to low-wage service roles or are forced to struggle with unemployment for long periods of time. At the same time, this shift in demand caused by automation leads to wages shifting toward the extremes and, consequently, further increases in income inequality.

The fundamental changes in the labor market necessitate the urgent implementation of new policies and strategies. The primary goal for Türkiye should be to create a comprehensive labor force map that also takes regional differences into account. This situation is expected to reveal the distribution of occupations based on routine and task type (manual/cognitive), thereby identifying sectors and occupations under threat from automation. This analysis will enable us to anticipate the effects of digitalization on employment and take proactive measures to protect the workforce at risk.

The job content of occupations varies depending on the level of development of the country. Therefore, specific to the Turkish labor market, there is a need for datasets that reveal the distribution of routine and non-routine tasks within the ISCO-08 occupational classification. However, in an environment rapidly transformed by artificial intelligence and automation technologies, analyses based solely on routine methods may be insufficient. Therefore, it is important to develop a new dataset that evaluates the dynamic characteristics of occupations, such as their susceptibility to artificial intelligence, complementarity, and resistance.

Routine manual occupations are at a high risk of automation. These types of jobs are becoming standardized and do not require extensive expertise. This situation necessitates shifting the focus of active labor force policies toward non-routine occupations, and the returns on such investments are expected to be relatively high. However, intense competition in sectors dominated by routine tasks may lead policymakers to adopt short-term solutions, such as policies aimed at reducing labor costs. This situation may economically delay the replacement of cheap labor with automation, causing sectors to lag behind in terms of productivity and competitiveness in the medium-to long-term. The high supply of labor in these occupational groups further exacerbates the threat's scale.

Non-routine occupations require high levels of experience, productivity, and wage levels; therefore, the process of specializing in these fields naturally takes longer. These characteristics necessitate that employment incentive policies be supported not only on a sectoral basis but also through targeted mechanisms tailored to occupational characteristics. However, the transformative impact of artificial intelligence on the labor market cannot be achieved through incentive mechanisms alone. It also necessitates comprehensive education and reskilling reforms that equip the workforce with skills that artificial intelligence can complement. The effective distribution of public resources and maximization of labor productivity will only be possible by adopting this holistic approach.

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