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THE INFORMATION TECHNOLOGY WORKFORCE IN THE AI ERA: A SYSTEMATIC REVIEW OF ROLES AND SKILLS

Mustafa Kemal MAYUK[1]

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Abstract

Artificial intelligence (AI) is transforming the labor market by reshaping workforce roles and skills. This study focuses on the IT workforce, aiming to systematically identify the roles addressed in the literature and the dimensions of their transformation. Guided by the PRISMA framework, search terms and time intervals were applied to Web of Science and Scopus, yielding non-duplicate 7,959 articles. After filtering for SSCI-indexed journals, 164 articles were reviewed descriptively and 19 analyzed through content analysis. Findings show that software development, data-related, and IT management roles are most affected by AI. Productivity gains emerge as the main positive effect, while negative and transformative impacts differ by role. Inexperienced software workers face displacement risks, data roles encounter heightened technical skill barriers, and IT management may experience reduced transparency. Transformative effects include the reshaping of technical and leadership skills as well as the expansion of ethical and technical responsibilities across IT roles.

Keywords: Artificial Intelligence, IT Workforce, Large Language Models, IT Management, Software Development, Data Analysis
Article Type: Review Article.

YAPAY ZEKÂ ÇAĞINDA BİLGİ TEKNOLOJİLERİ İŞGÜCÜ: ROLLER VE YETENEKLERE İLİŞKİN SİSTEMATİK BİR İNCELEME

Atıf/©: Mayuk, M. K. (2025). Yapay zekâ çağında bilgi teknolojileri işgücü: Roller ve yeteneklere ilişkin sistematik bir inceleme. *Uluslararası Yönetim Araştırmaları ve Uygulamaları Dergisi*, *4*(2), 1-22.

Özet

Yapay zekâ (YZ), işgücü piyasasını dönüştürerek işgücünün rollerini ve becerilerini yeniden şekillendirmektedir. Bu çalışma, bilgi teknolojileri (BT) işgücüne odaklanarak literatürde ele alınan rolleri ve dönüşüm boyutlarını sistematik biçimde ortaya koymayı amaçlamaktadır. PRISMA çerçevesi doğrultusunda geliştirilen arama terimleri ve zaman aralıkları Web of Science ve Scopus veri tabanlarında uygulanmış, mükerrer olmayan 7.959 makale elde edilmiştir. SSCI indeksli dergilerle sınırlandıktan sonra 164 makale betimsel olarak incelenmiş, 19 makale içerik analiziyle değerlendirilmiştir. Bulgular, yazılım geliştirme, veriyle ilgili ve BT yönetimi rollerinin YZ'den en çok etkilenen alanlar olduğunu göstermektedir. Verimlilik artışı başlıca olumlu etki olarak öne çıkarken, olumsuz ve dönüştürücü etkiler role göre farklılaşmaktadır. Deneyimsiz yazılım çalışanları iş kaybı riskiyle, veri rolleri artan teknik beceri bariyerleriyle, BT yönetimi ise şeffaflık azalmasıyla karşı karşıyadır. Dönüştürücü etkiler, teknik ve liderlik becerilerinin yeniden şekillenmesi ile etik ve teknik sorumlulukların genişlemesi olarak görülmektedir.

Anahtar Kelimeler: Yapay Zekâ, BT İşgücü, Büyük Dil Modelleri, BT Yönetimi, Yazılım Geliştirme, Veri Analizi
Makale Türü: Derleme Makale.

1. INTRODUCTION

The impact of artificial intelligence (AI) on labor markets revives a classic technological dialectic: the tension between human productivity enhancement and labor displacement. The primary aim of this study is to contribute to establishing a scientific foundation for discussions regarding the relationship between labor dynamics and technology. While scientific literature frequently addresses the impact of technology

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on the labor market in general terms, in practice, different technological domains affect various occupational sectors to differing extents (Wang et al., 2024). A fundamental technological divergence stems from the core skills used in different professions: automation and robotics replace experience-based manual labor, characteristic of blue-collar work, whereas AI (particularly generative AI) augments the knowledge- and education-based foundation of white-collar roles (Autor et al., 2003; Acemoglu & Restrepo, 2020; Frey & Osborne, 2017). Research confirms a fundamental divergence: robotics primarily transforms physical labor, while generative AI reshapes mental work. However, reducing mental workers to a single group is hardly feasible. This distinction aligns with Acemoglu & Restrepo's (2019a) task-based framework, which suggests that automation technologies primarily displace routine tasks in white-collar occupations through substitution effects, while having more limited impacts on non-routine, cognitive-intensive work. A more precise conceptual alignment associates non-routine, cognitive-intensive tasks with the augmentative capabilities of generative AI, rather than with automation-prone technologies.

The reason this study focuses on information technology (IT) labor is the notion that the IT workforce exhibits certain vulnerabilities in the face of AI and automation technologies. In recent years, there have been researches and reports supporting this view (Eloundou et al., 2023; Kochhar, 2023; Muro et al., 2025). A key reason for this is that, unlike many certified professions that rely on formal education and institutionalized credentialing, the IT field remains weakly professionalized and largely dependent on practical, experience-based know-how. Its occupational boundaries are relatively fluid, with limited professional organization and certification mechanisms (Barley, 1996; Bechky, 2003). Moreover, IT labor represents a high-skill and high-wage segment of the workforce (U.S. Bureau of Labor Statistics, 2024), increasingly constituting a major cost component in organizations. A critical consideration is the recognition that IT labor should not be conceptualized as a monolithic entity. IT constitutes a multi-layered ecosystem encompassing diverse areas of specialization, roles, and non-technical processes (Heeks, 2008). One objective of this study is to examine how the scientific literature addresses the impact of AI on IT in light of this heterogeneity.

The term AI encompasses a broad range of technologies, from classical machine learning to deep neural networks, with its meaning tied to the technological infrastructure of each era (Benjamins & Salazar, 2020). This study defines AI's boundaries based on technological elements within the relevant time range, using the starting year of current AI developments for literature filtering. Criteria for application within the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework were established through the operationalization of AI definitions and IT roles as outlined in the theoretical framework. The results section addresses the study's limitations, theoretical and practical contributions, and provides recommendations in two areas: (1) future research examining the technology-labor market relationship, and (2) policy and managerial guidance for education, technology, and employment stakeholders on AI-induced disruptions.

2. THEORETICAL FRAMEWORK

Establishing criteria for implementing a systematic review screening is essential. This section explains the theoretical background related to IT roles and AI, which represent the two variables in the study. Although these concepts are widely used, their meanings can be highly variable and broad. This section, which includes brief definitions of the concepts, aims to identify the subtopics that are examined in relation to the concepts. Subtopics that determine criteria and search queries, are also presented based on the literature. The criteria may be considered as IT roles or skills and what is meant by the concept of artificial intelligence.

2.1. IT, ICT and Information Security (InfoSec)

Information and communication technologies (ICT) are an expanded version of information technology (IT), which also includes communication technologies. IT alone refers mainly to work processes on hardware, software, and data management systems. IT primarily focuses on running software applications on hardware systems, processing and storing the data they produce. ICT, on the other hand, extends IT by incorporating communication technologies that provide access to these resources and enable data transmission and interaction between them (TechTarget, 2025; Wikipedia: Information and communications technology, 2025).

Information security is not solely comprised of technical measures; it also includes non-technical processes such as the implementation of security policies, monitoring compliance frameworks, and raising awareness. Information security and IT security are often evaluated together, as the goal of protecting information is largely dependent on the security of the IT infrastructure. However, information security goes beyond access control and aims to ensure the confidentiality, integrity, and availability of information. Although the aspects of information security that are addressed jointly with IT are evaluated under a separate heading as IT security, the literature treats information security as intertwined with technology because the focus of information security is IT assets (International Organization for Standardization [ISO], 2005; von Solms & van Niekerk, 2013).

This study examines aspects of information technology (IT), including certain core roles related to communication technologies, but its scope does not primarily extend to the broader information and communication technology (ICT) domain. Since information security is intertwined with information technologies and is mostly referred to as IT or ICT security, topics related to information security have also been included in the examination.

2.2. IT as a Profession

IT is not a professional field with homogeneous roles where a single type of skill or education is sufficient. It is generally a broad term encompassing various computer-related activities and processes based on different skill sets, experiences, or certified trainings. Defining the profession or measuring the competence of someone working in the IT field is not easy due to the difficulty of defining specific parameters. There is much debate about comparing IT professionals to other well-known professions, as it is common to see many people working in this sector who do not have a certificate or license, but only experience. This does not mean that IT professionals are unimportant, but the statue of the profession may be seen as weak because certification is not mandatory. Software development, being largely related to computer science, appears to have a higher potential to be recognized as a profession. However, there are a significant number of software developers working in the sector without certification (Weckert & Adeney, 2013).

Due to the difficulty of defining the IT profession and the fact that it is a general term covering various activities, it is necessary to identify the roles or skills associated with these activities (Weckert & Adeney, 2013). IT activities can generally be defined as the workflow of developing or installing software, applications, or modules thereof, and operating and delivering them to users with high uptime without performance degradation. This lifecycle is often expanded to include security, identity, and compliance processes (ISO, 2008). Such a job description may require numerous IT employees and teams, depending on the size of the company (Organization for Economic Co-operation and Development [OECD], 2025).

2.2. Revealing of IT Employee Roles

Many studies in the field of business and management approach IT as a “black box.” Within this perspective, firms are assumed to invest in IT and subsequently generate certain outputs, with efficiency being evaluated based on these outcomes. However, the fundamental mechanisms through which IT contributes to productivity and value creation are often left unexplored (Zand et al., 2015). Before identifying the roles and skills of IT employees, it is necessary to understand the roles of IT.

Early studies conceptualized the role of IT within organizations primarily in terms of information processing. Within the framework of Organizational Information Processing Theory (OIPT), IT is seen as a tool to improve and accelerate existing processes by increasing the organization's information processing capacity (Galbraith, 1974; Tushman & Nadler, 1978). In this sense, OIPT largely attributes an efficiency-oriented role to IT. The Resource-Based View (RBV) approach revealed that IT not only plays a role in improving processes and increasing efficiency, but also has a transformative role that gives companies a competitive edge (Barney, 1991). The evolution of technology over time, from serving primarily a supporting function to becoming a core organizational task, has given rise to new approaches concerning the role of IT (Brynjolfsson & Hitt, 2000). According to the Resource-Based View (RBV), IT has evolved beyond an operational tool and now holds a strategic position in organizations. However, this does not imply that IT has lost its operational and efficiency-oriented functions. Rather, for companies, IT constitutes an organizational resource with a hybrid role. As a result of synthesizing these two perspectives, IT can be understood as encompassing primary roles such as information processing and communication, secondary roles such as automation and coordination, tertiary roles such as integration and transformation, and a quaternary role of innovation (Zand et al., 2015).

The organizational roles of IT, as classified by Zand et al. (2015), provide a valuable framework for understanding how technology creates business value. However, a complementary research stream focuses on the roles of IT workers, examining how professionals such as developers, managers, analysts, and executives contribute to the fulfillment of these organizational functions. In this sense, organizational IT roles and IT workers' roles can be seen as interrelated dimensions of digital value creation. There are numerous studies that categorize IT workers using different approaches. For example, Devolder (2010) classifies them as planners, budgeters, technicians, and educationalists, whereas Reinhardt et al. (2011) identify ten distinct roles, including controllers, helpers, learners, linkers, networkers, organizers, retrievers, sharers, solvers, and trackers.

This study examines the practical implications of the roles of IT and IT workers as theoretically conceptualized in the literature. For this type of analysis, it is also necessary to consult industry resources. For instance, a Cisco (2024) report categorizes IT job roles into broad domains such as software development, cybersecurity, data science, infrastructure, and operations, whereas the International Standard Classification of Occupations (ISCO-08) published by the International Labor Organization provides a more detailed and systematic classification of job roles (International Labor Organization [ILO], 2012). The ISCO-08 framework defines traditional IT roles such as system administrators, database administrators, network administrators, software and system analysts, support technicians and software developers or programmers (ILO, 2012). In contemporary practice, however, these roles have expanded, and organizations increasingly employ system, database, network, and software engineers, who assume additional responsibilities in system design and architecture (Indeed Editorial Team, 2025; Zippia, 2024; Franklin Fitch, 2024).

The accelerating pace of developments in IT has resulted in ISCO-08, developed in 2008 and published in 2012, becoming increasingly outdated (ILO, 2012). While the traditional IT roles described in ISCO-08 remain relevant, recent transformations in areas such as cloud computing, data-driven technologies, and the Internet of Things (IoT) have created the need for additional, specialized roles. On the one hand, the growing importance of information security within IT demonstrates that security-related roles should be included in the classification of IT professions. The Bee-inspired Employment and Expertise Taxonomy (BEET), proposed to address the limitations of ISCO-08, also incorporates a wide range of contemporary IT roles. Among the most prominent are DevOps, Site Reliability Engineering (SRE), cloud engineering, platform engineering, middleware engineering, IT architecture, data science, data engineering, IoT engineering, cybersecurity engineering as well as software testing and quality assurance (QA) engineering, which represent some of the leading IT professions today (Valverde-Rebaza et al., 2025). The roles and responsibilities that emerge when traditional and modern classifications are shown in Table 1 and Table 2.

Table 1. Traditional IT Employee Roles and Responsibilities

Role	Definition/What They Do
System Administrator/Engineer	Installs and maintains operating systems and servers including its disk storage layer
Database Administrator/Engineer	Installs, manages, and secures databases; ensures backups
Network Administrator/Engineer	Manages network infrastructure, design network topologies
Software Developer/Programmer	Designs, codes, and maintains software applications
Support Technician/Engineer	Solves technical problems of end-users
Software and System Analyst	Bridge business needs and technical solutions

Table 2. Modern IT Employee Roles and Responsibilities

Role	Definition/What They Do
DevOps Engineer	Integrates software development and operations, builds deployment pipelines using automation
Site Reliability Engineer (SRE)	Ensures high uptime, minimum faults, low latencies of applications using monitoring and observability solutions
Cloud Engineer	Designs, installs and maintains cloud infrastructure
Platform Engineer	Designs, installs and maintains software-based platforms for software development that enables integrations and automations
Middleware Engineer	Works on integrations between applications and databases
Data Scientist	Prepare data for machine learning modelling and creates models
Data Engineer	Provides data streaming and pipelining for data scientists
Software QA/Test Engineer	Automates testing software using several tools, ensures quality though pipeline
Cybersecurity Engineer	Designs, implements, and maintains security measures to protect systems, networks, and data from cyber threats

Although not explicitly listed in the tables, both traditional and modern managerial positions such as IT Manager, IT Leader, and Chief Technology Officer (CTO) are considered integral parts of the IT workforce.

2.3. Definition of AI

Artificial intelligence (AI) is a very broad field of computer science with a history dating back to the 1950s. For many years, humans have aimed to design systems that learn, solve problems, and adapt in ways like human intelligence. While this goal is the conceptual definition of artificial intelligence, what is meant by artificial intelligence has varied historically. Artificial neural networks, which date back to very early years, have a data-driven working mechanism, unlike rule-based artificial intelligence systems. Although IBM Deep Blue's defeat of Kasparov in 1997 appeared to be a victory for the rule-based approach, it was thanks to deep learning algorithms developed in the early 2000s because of more intensive work on artificial neural networks that computers were able to truly perform human abilities such as image and natural language processing (Rai, 2024).

Advances in natural language processing have been one of the most influential factors in reinforcing the belief that artificial intelligence has truly been realized. Transformer-based large language models, built on deep learning as an advanced form of artificial neural networks, have introduced the concept of generative artificial intelligence and expanded machine capabilities beyond traditional tasks. Although this association is not entirely precise, in contemporary discourse artificial intelligence is often used interchangeably with large language models and generative AI, reflecting their dominant role in shaping current perceptions of the field (O'Neill & Connor, 2023). This study has also taken this perception into account as part of the content of the artificial intelligence concept.

Technically, any discussion of large language models or generative artificial intelligence begins with the introduction of the transformer architecture. The transformer architecture was first proposed in 2017 by Vaswani et al., a group of researchers from Google Brain/Google Research, in their seminal paper "Attention Is All You Need" (Vaswani et al., 2017). After 2017, artificial intelligence has largely come to denote large language models and generative AI. Research activity has intensified steadily since then and remains ongoing. For this reason, the present study employs the 2017–2025 period as a benchmark for systematic publication screening. Today, although the term AI is most used to denote large language models and generative artificial intelligence, these technologies are scientifically situated within the hierarchical clusters of machine learning, artificial neural networks, and deep learning. Accordingly, these underlying concepts must also be considered in the literature review.

3. LITERATURE REVIEW

The increasing number of applications for artificial intelligence has led to a rise in research questioning its impact on the workforce. Its effects on the labor market, how it transforms the workforce, and expectations for the future are frequently discussed topics. Considering that the impact of IT on the workforce is examined largely through role-based analyses, the methodological framework of this study determined its search criteria in alignment with IT roles.

The OECD (2024) reports that, despite widespread fears of automation, there is so far little evidence that artificial intelligence has led to overall job losses. Instead, AI primarily reshapes tasks within occupations, especially in high-skilled jobs, and generates new demands for reskilling and upskilling rather than eliminating entire professions. In a similar vein, Ünal & Kılınç (2024), through a systematic review of generative AI applications in business, highlight that while such technologies can enhance productivity and creativity in the short term, they also pose ethical, legal, and organizational risks, making their impact a "double-edged sword." At the policy level, Mehrotra et al. (2024) underline this dual nature by stressing that AI entails significant short-term risks of displacement and inequality, but in the long run holds the potential to boost productivity and create new employment opportunities, provided adequate governance and international cooperation are in place. Complementing these perspectives, Sengupta (2025) provides firm-level evidence showing that in advanced economies AI shocks initially depress wages before recovering with productivity gains, while in emerging and developing economies the reverse occurs—short-term wage increases followed by longer-term declines—indicating that the effects of AI on labor markets are heterogeneous across contexts and time horizons. Taken together, these studies suggest a common pattern: while AI adoption tends to generate risks in the short term, especially in the form of displacement and inequality, it is also widely expected to deliver productivity gains and new opportunities in the longer run.

Recent debates converge on the view that artificial intelligence will profoundly reshape the future of work, though in ways that are far from predetermined. Acemoglu & Restrepo (2019b) argue that the current trajectory of AI is biased toward automation, substituting machines for human labor in routine and even cognitive tasks. This trend risks stagnating labor demand, reducing the labor share of income, and exacerbating inequality, particularly if automation generates only limited productivity gains. Historical evidence suggests that labor markets thrive not simply when tasks are automated, but when new, labor-intensive tasks are simultaneously created. Similarly, an International Labor Organization study (Ernst et al., 2018) highlights both the opportunities and risks embedded in AI adoption. On the one hand, AI-driven digital technologies can lower capital costs, raise productivity, and expand access to higher-quality employment, even in developing economies. On the other hand, without deliberate policies, these gains may be captured by a small number of firms, reinforcing market concentration and deepening inequality. The report emphasizes that the distinct character of AI—targeting mental rather than manual tasks—poses unique challenges compared with earlier waves of mechanization. Taken together, these perspectives suggest that the impact of AI on labor markets will depend less on technological inevitability than on institutional and policy responses. If AI development continues to focus narrowly on automation, the likely outcomes are weaker labor demand and rising inequality. Conversely, if innovation is steered toward creating complementary tasks and inclusive productivity gains, AI could support new forms of work and more equitable growth.

The contrasting positive and negative potentials of artificial intelligence have been widely highlighted in recent studies. Artificial intelligence is increasingly transforming the business world by reshaping blue- and white-collar professions, redefining workers' skills, and changing organizational practices. Its effects are contradictory: While artificial intelligence can increase productivity, creativity, and decision-making, and even create new forms of employment, it also poses risks of job loss, skill erosion, privacy concerns, and increased inequality. Furthermore, its integration into the workplace highlights the need for ethical governance, transparent data usage, and continuous reskilling to ensure trust and sustainability. Overall, these findings show that artificial intelligence is both a disruptive challenge and a source of long-term opportunities for both workers and organizations (Özer et al., 2024; Kulkarni et al., 2024; Farhan, 2023).

When focusing specifically on the IT workforce, studies emphasize that AI carries negative, transformative, and supportive dimensions. An industry report led by Cisco, in collaboration with major technology companies such as Accenture, G42, Google, IBM, Intel, and Microsoft, provides a comprehensive picture of these dynamics. The report shows that 92 percent of IT roles are expected to undergo significant transformation as AI adoption accelerates. Entry- and mid-level positions are particularly vulnerable, with around 37–40 percent facing a high risk of disruption. On the negative side, traditional skills such as basic programming, routine documentation, and conventional data management are projected to lose value. At the same time, AI is seen as transformative, driving demand for new competencies including AI literacy, data analytics, prompt engineering, ethical AI practices, and human–AI collaboration. Finally, the supportive role of AI emerges in the form of opportunities for reskilling and upskilling, which the report stresses as urgent priorities. It calls for collective action from industry, governments, and educational institutions to establish global standards, create sustainable learning ecosystems, and ensure that the workforce is equipped to adapt to rapid technological change (Cisco, 2024).

Numerous other studies have revealed the positive, negative, and transformative effects of AI on the IT workforce. In terms of positive impacts, AI education has been shown to strengthen workforce readiness; Chen & Zhang (2024) demonstrate that introductory AI courses enhance students' conceptual understanding, literacy, and empowerment. Within organizational settings, AI adoption in human resource management improves data-driven decision-making and efficiency, as reflected in the study by Sharma et al. (2025) on HR analytics in the IT sector. Similarly, Brauner (2023) contribute by developing a competence framework for AI professionals, which formalizes skill sets and helps establish professional standards. Nonetheless, negative aspects are also evident: Kulchan et al. (2025) reveal persistent skill gaps in fundamental technical areas such as version control systems, raising concerns that wider AI adoption could exacerbate workforce inequalities. In addition, Dwivedi et al. (2025) emphasize that while generative AI offers new opportunities for global IT management, it simultaneously introduces uncertainties in governance, ethics, and employee role clarity. These findings confirm that AI is not only producing incremental changes but is also acting as a transformative force—redefining workforce competencies, reshaping organizational practices, and altering the interconnections between education, skills, and employment.

AI is transforming the IT workforce by automating routine roles, creating new specialties, and requiring rapid reskilling. Johnson (2025) notes that entry-level developers and Tier-1 IT support staff are most at risk as AI tools replace coding and troubleshooting tasks. Yet, demand is rising for advanced roles in cybersecurity, machine learning, and AI governance, widening the skills gap and polarizing the workforce. To adapt, organizations must invest in AI literacy, ethical governance, and reskilling programs to ensure human expertise complements rather than competes with automation.

Recent studies that are conscious of the fact that what is increasingly meant by AI is generative AI (GenAI) highlight both its promises and its risks for the workforce. Bonin et al. (2025) show that nearly all IT professionals now employ GenAI tools such as ChatGPT and GitHub Copilot, experiencing measurable gains in productivity and efficiency, while at the same time reporting heightened concerns over job security and output reliability. Similarly, Ünal & Kılınç (2024) conceptualize GenAI as a "double-edged sword," noting that its ability to generate novel outputs can enhance business productivity, efficiency, and competitiveness, but also brings challenges related to bias, legal compliance, ethical dilemmas, and data privacy. Together, these findings underline that in today's organizational and IT contexts, references to AI largely imply GenAI, which operates as both a transformative enabler and a disruptive force requiring careful governance. According to the OECD (2024), GenAI is expected to exert some of its strongest effects on knowledge-intensive sectors such as IT, telecommunications, and finance. In IT specifically, GenAI poses a high risk of automating entry-level tasks while simultaneously driving demand for advanced technical and complementary skills. This dual impact underscores both the opportunities for productivity gains and the risks of workforce polarization, making reskilling policies particularly urgent in the IT domain (OECD, 2024).

The literature generally evaluates the effects of AI on the labor market in terms of both positive and negative outcomes. On the negative side, emphasis is often placed on the reduced dependence on human labor, downward pressure on wages, and the potential for increased unemployment. In contrast, positive perspectives highlight productivity gains and the emergence of new occupational areas. When narrowed to the IT and IT workforce, however, the discussion expands beyond these general effects to include the transformative impact of AI on existing skills and roles. In this context, the literature also identifies facilitating and supportive effects—such as enhanced efficiency and decision-making—as part of the positive dimension. At the same time, the negative side is extended to issues of skill deterioration, workforce inequality, and ethical concerns, which underscore the complex and multidimensional nature of AI's influence on IT labor markets.

The literature takes a more tiered approach when examining the effects of AI on IT employment. It emphasizes that entry-level tasks are more susceptible to automation than higher-level, role-based responsibilities. Consequently, advanced positions requiring complex technical and managerial skills are more likely to be complemented and even enhanced by GenAI, whereas routine and repetitive functions face a greater risk of displacement. This distinction illustrates the uneven distribution of AI's effects in IT labor markets, where entry-level workers encounter higher levels of job insecurity compared to their more specialized colleagues (OECD, 2024).

4. RESEARCH

The research framework of the study is presented in this chapter. The significance and objectives of the research are first summarized, and the study is situated within a broader academic and practical context. The research questions to be addressed are then explained, and the methodology is described in detail, including the systematic review process carried out in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Finally, the key findings obtained from the literature analysis are summarized, thereby providing the basis for the subsequent discussion and interpretation.

4.1. Purpose and Importance of the Research

Although the literature review reveals numerous investigations into the impact of AI on the IT workforce, role-specific analyses remain limited. This study further refines the definition of AI and addresses its impact on IT roles through a systematic literature review. This study seeks to assess the extent to which the impacts of AI have been scientifically examined in the existing literature, to identify IT roles that are disproportionately represented or overlooked, and to explore the specific types of impacts that the literature attributes to AI on these roles. Given that this study employs a systematic literature review to examine the impact of AI on the IT workforce, the research questions guiding the analysis can be formulated as follows:

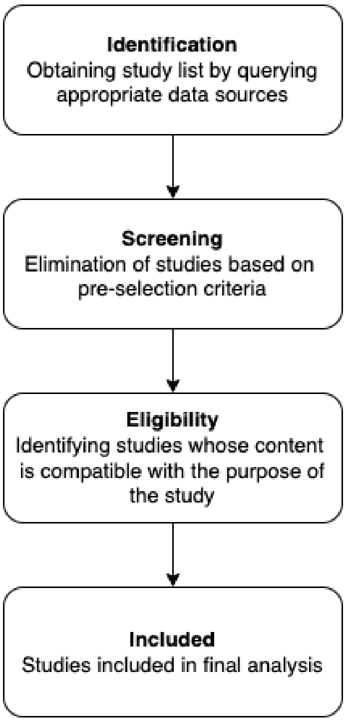
i. Which specific IT roles are addressed in the existing body of research?
ii. What impacts (positive, negative, transformative) of AI on the IT workforce are revealed in the studies and in what dimensions?

AI is increasingly making its impact felt across all aspects of life and continues to be the subject of considerable debate. Scientific studies attempt to predict how individuals will be affected by this technological revolution, highlighting strengths and vulnerabilities and offering recommendations. This study seeks to examine the strengths and weaknesses of research focusing on IT as a specific segment of the workforce. Such studies help reduce uncertainty, provide a roadmap, and play a vital role in guiding policymakers, decision-makers, and leaders.

4.3. Research Method

This study is a systematic literature review and applied Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. PRISMA provides a standard that ensures systematic literature reviews and meta-analyses are conducted in a reproducible, transparent and open manner (Page et. al., 2021). Figure 1 shows the stages of the PRISMA process.

Figure 1. Stages of PRISMA



4.3.1. Data Sources and Search Strategy

Web of Science and Scopus databases were used as data sources, and filters for IT roles were tailored to each database. Search criteria were defined for inclusion and exclusion, date range, language, and publication type. Inclusion terms were created by combining terms representing IT roles with terms representing AI using the AND operator. Terms that studied the impact of AI but did not represent the workforce were also excluded.

In the section where the theoretical background is explained, it is stated that each term is expressed according to the technology behind artificial intelligence, and that the concept of artificial intelligence as it is perceived today matured after the scientific studies conducted in 2017 (Vaswani et al., 2017; O'Neill & Connor, 2023). Taking this determination as a reference, the study defined the search criteria within the date range of 2017–2025. As the study aimed to include only research with relevant findings, articles were filtered by study type, and English was set as the publication language in the search queries. The IT roles included in the search criteria comprised both traditional and modern roles, as presented in Tables 1 and 2. Similar roles were grouped and connected within a single query using the OR operator to ensure no roles were excluded. These role expressions were then combined with the AI-related terms using the AND operator: ("artificial intelligence" OR "AI" OR "LLM" OR "large language model*" OR "generative AI" OR "machine learning" OR "ML" OR "deep learn*" OR "neural network*"). The exclusionary query ("education" OR "training" OR "health" OR "medical" OR "law" OR "legal" OR "government" OR "public sector" OR "public administration" OR "policy" OR "regulation" OR "governance") was applied to filter out studies addressing the effects of AI beyond the workforce. Table 3 shows queries for the IT roles in detail.

Table 3. Search Queries for IT Roles

Queries for IT Roles
"software engineer*" OR "computer programm*" OR "software development" OR "software coding" OR "software test*" OR "QA engineer*" OR "software quality assurance" OR "software analys*"
"system admin*" OR "system engineer*" OR "it infrastructure*" OR "support engineer*" OR "support technic*"
"devops engineer*" OR "devops admin*" OR "cloud admin*" OR "cloud engineer*" OR "platform admin*" OR "platform engineer*" OR "middleware engineer*" OR "site reliability engineer*" OR "SRE engineer*"
"database admin*" OR "database engineer*" OR "db admin*" OR "db engineer*" OR "db management"
"network* admin*" OR "network* engineer*" OR "computer network*" OR "IoT engineer*"
cyber security engineer*" OR "security engineer*" OR "network security engineer*" OR "cyber security admin*" OR "security admin*" OR "network security admin*"
"data engineer*" OR "data scientist" OR "data science process*" OR "data analyst" OR "data analyzer"
"IT manager" OR "IT management" OR "IT leader*" OR "chief technology officer" OR "CTO"

As a result, the studies included in the scope of this research were required to meet the following conditions: to be published between 2017 and 2025, to be in the form of an article, to be written in English, to contain IT role terms, to include AI concept terms, and to exclude the defined exclusionary terms. Below are examples from Web of Science and Scopus databases for software-related roles.

An example of a Web of Science query:

TS=(("software engineer" OR "computer programm*" OR "software development" OR "software coding" OR "software test*" OR "QA engineer*" OR "software quality assurance" OR "software analys*")*

AND ("artificial intelligence" OR "AI" OR "LLM" OR "large language model" OR "generative AI" OR "machine learning" OR "ML" OR "deep learn*" OR "neural network*")*

NOT ("education" OR "training" OR "health" OR "medical" OR "law" OR "legal" OR "government" OR "public sector" OR "public administration" OR "policy" OR "regulation" OR "governance"))

AND PY=(2017-2025)

AND DT=(Article)

AND LA=(English)

An example of a Scopus query:

TITLE-ABS-KEY(("software engineer" OR "computer programm*" OR "software development" OR "software coding" OR "software test*" OR "QA engineer*" OR "software quality assurance" OR "software analys*")*

AND ("artificial intelligence" OR "AI" OR "LLM" OR "large language model" OR "generative AI" OR "machine learning" OR "ML" OR "deep learn*" OR "neural network*")*

AND NOT ("education" OR "training" OR "health" OR "medical" OR "law" OR "legal" OR "government" OR "public sector" OR "public administration" OR "policy" OR "regulation" OR "governance"))

AND PUBYEAR > 2016 AND PUBYEAR < 2026

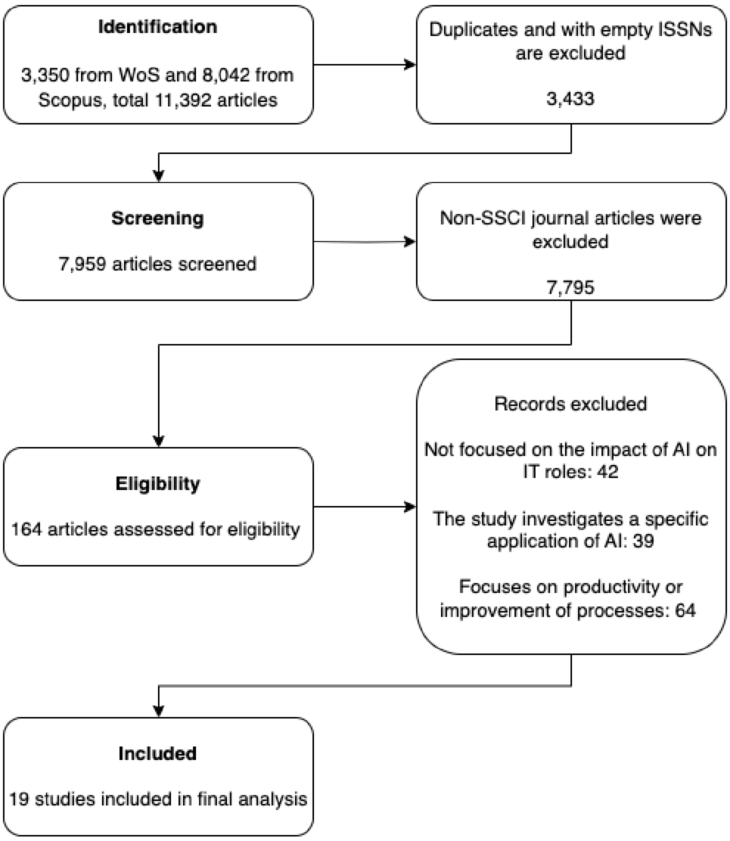
AND (LIMIT-TO(DOCTYPE, "ar"))

AND (LIMIT-TO(LANGUAGE, "English"))

4.3.2. PRISMA Flow Diagram of Study Selection

Figure 2 presents the PRISMA processes for the studies covered in this study.

Figure 2. Stages of PRISMA in this study



The database search yielded 11,392 articles, of which 3,350 were retrieved from Web of Science and 8,042 from Scopus. After removing duplicates and records without ISSN information, 7,959 articles remained. Restricting the dataset to articles published in SSCI-indexed journals resulted in a final set of 164 articles. Considering studies that treat artificial intelligence as an independent variable within the social sciences, 19 articles were identified as relevant to the subject of this research.

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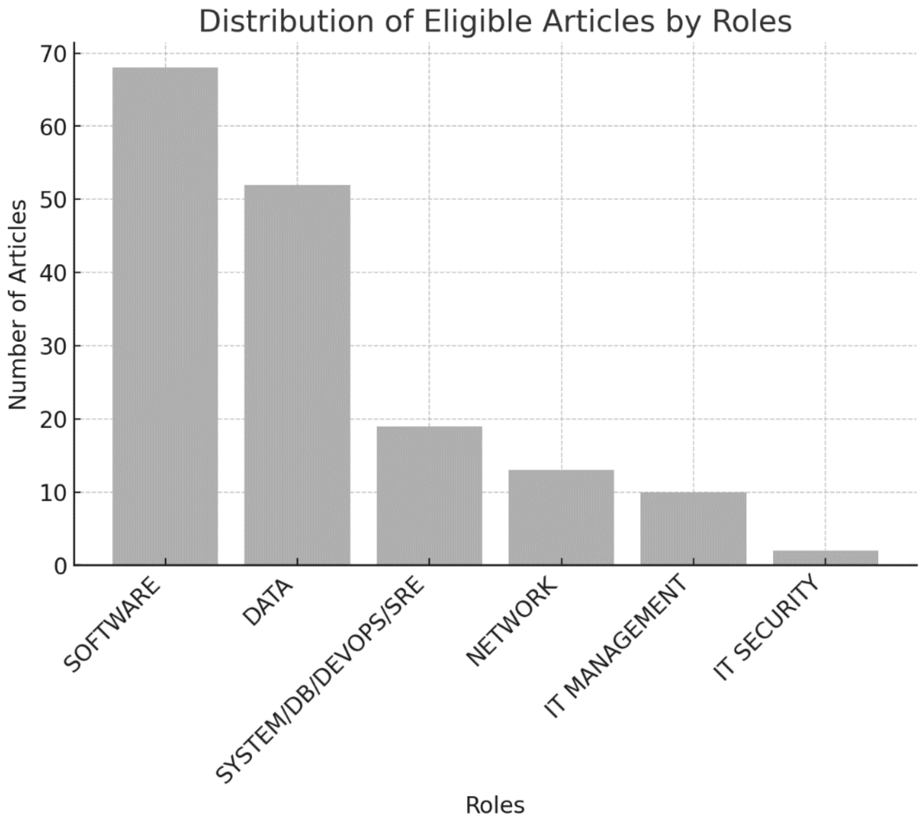
Artificial intelligence represents a phenomenon of growing scholarly interest, and in recent years it has increasingly been adopted not only as an object of study but also as a methodological tool in research. On the other hand, studies that apply artificial intelligence to evaluate efficiency and measure processes have also become increasingly common. For this reason, the number of articles included in this study, which attempts to understand the impact of artificial intelligence on the IT workforce, has decreased from 164 to 19. This study investigated the specific IT roles emphasized in these 19 articles and assessed the extent to which the effects of IT were addressed in relation to those roles.

4.4. Findings and Discussion

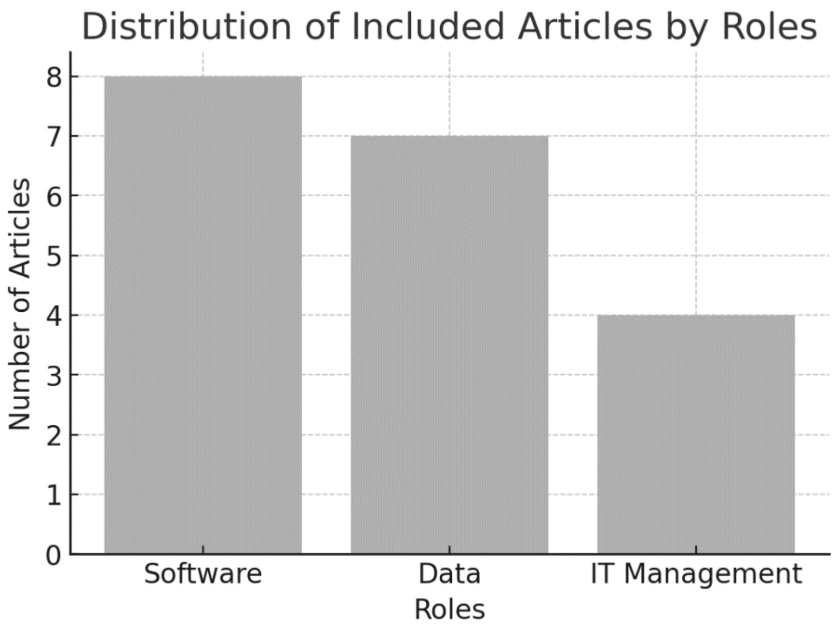
The findings can be presented in two stages: descriptive and research focused. The descriptive findings report the frequency and number of 164 eligible and 19 included studies. With respect to the research topic, a total of 19 articles were identified to determine the roles examined and the extent of the impacts addressed. Distribution of 164 eligible articles by roles shown in Figure 3.

Figure 3. Distribution of eligible articles by roles



Similar roles that operate by connecting to systems—such as systems engineering, DevOps, database administration, and site reliability engineering (SRE)—were grouped into a single category due to their limited and fragmented representation. In contrast, IT security, although also small in number, was treated as a distinct role and therefore not merged into this category. All other roles correspond directly to those filtered in Table 3. When the role-based distribution of included articles is examined, it appears that only software, data, and IT management roles are covered. Of the 19 articles addressing the impact of AI on the IT workforce and roles, which is the focus of this study, eight focus on software, seven on data, and four on IT management roles. Figure 4 illustrates this distribution.

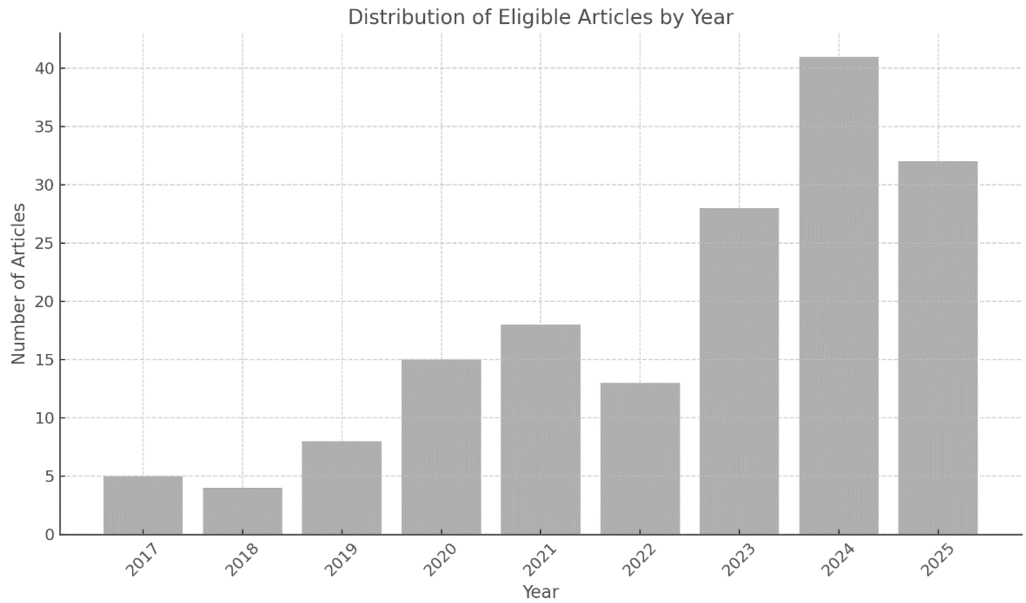
Figure 4. Distribution of included articles by roles

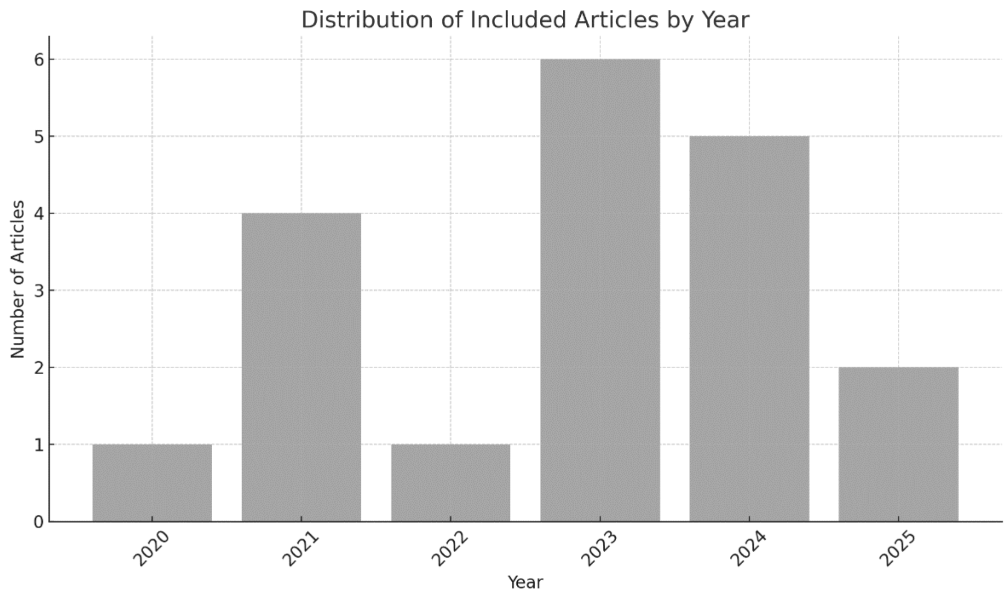


Role-based numbers indicate that areas related to IT infrastructure and engineering are understudied and are not sufficiently included in the IT roles that will be affected by AI. When the most frequently studied role category—software—is considered, 68 of the 164 eligible articles address software-related roles. Among the 19 included articles, eight focus on software roles. A more detailed examination reveals that, within the eligible set, 47 of the 68 software-related articles are concerned with software development, while 21 address software testing or QA roles. Of the included articles, six specifically focus on software development. As the second most frequently studied role category, data-related roles are addressed in 52 of the 164 eligible articles. Among the 19 included articles, seven focus on data roles. A closer examination of the eligible set shows that 29 articles investigate data science, 18 focus on data analysis, and five explore data engineering. Within the included articles, four are concerned with data science and three with data analysis. While a large proportion of articles examining software roles specifically focus on software development, articles examining data roles focus almost equally on data science and data analysis. Data engineering is less prevalent among data roles, as is the case with roles like infrastructure, operations, and systems engineering across IT. Regarding IT management roles, 10 of the 164 eligible articles were related to this category, while four of the 19 included studies addressed IT management. Proportionally, the representation of IT management is higher among the included articles than among the eligible set. While the share of IT management articles does not even reach 1% of the eligible studies, it accounts for as much as 21% of the included articles.

When the number of articles is considered by year, it is observed that eligible studies were published between 2017 and 2025, thereby defining the temporal scope of this systematic literature review. The volume of publications increased notably after 2017, while the included studies are concentrated in the period after 2020. The release of GPT-3 in 2020 was identified as a turning point in the field of artificial intelligence (Brown et al., 2020), as it marked the beginning of intensified discussions regarding whether AI—particularly in software-related domains—could replace parts of the IT workforce (GitHub, 2021; Eloundou et al., 2023). The number of included articles by year is also consistent with the beginning of study on this subject. Figure 5 shows the numbers by years.

Figure 5. Number of eligible and included articles by year





By examining the contents of included articles, it is possible to synthesize the findings regarding the effects of artificial intelligence on software, data and IT management roles. A synthesis of studies on software-related roles demonstrates that artificial intelligence exerts a multifaceted impact on software development. In the literature, tools such as GitHub Copilot and ChatGPT are consistently linked to productivity gains, particularly through the automation of repetitive coding tasks and the provision of learning support for junior developers (Eshraghian et al., 2025; France, 2024). At the same time, they are reshaping professional identities by shifting the role of software engineers from routine code production toward oversight, complex problem-solving, and the integration of AI-generated outputs (Komp-Leukkunen, 2024). Several studies highlight that IT professionals working in software raise concerns regarding reliability, accountability, quality assurance, intellectual property, and ethical standards, thereby underscoring the governance challenges associated with AI adoption (López-Gil & Pereira, 2025; Wang et al., 2021; Widder & Nafus, 2023). Overall, the evidence converges on the conclusion that AI is not replacing software engineers; rather, it is redefining their required skill sets and restructuring the nature of their work (Jiang et al., 2020; Royal, 2023). Nevertheless, the studies also emphasize that employment risks are more pronounced in simpler and more routine tasks—such as coding unit tests or documentation—that are typically performed by novice professionals (Eshraghian et al., 2025; Komp-Leukkunen, 2024).

Evidence from studies on data-related roles shows that artificial intelligence is altering the practices and expectations of data work. AI-driven tools are accelerating data analysis, increasing efficiency but also reducing the demand for entry-level research workforces (Atkinson, 2023). At the analytical level, deep learning-enabled extensions to structural equation modeling provide data analysts with more flexible and powerful modeling approaches while also raising barriers for those lacking advanced technical skills (van Kesteren & Oberski, 2021). Research on AI-enabled data work highlights the tensions between technical optimization and professional values, highlighting the growing importance of ethical awareness and responsible AI applications in data-intensive roles (Bastian et al., 2021; Møller & Thylstrup, 2024; Domínguez et al., 2024). Storing, processing, and preparing large amounts of frequently updated data is also crucial for the accuracy of findings in data analysis (Fridman et al., 2023). Research suggests that AI is increasing the need for technical talent in data science and data analyst roles, and that existing roles are insufficient (Fu et al.,2024; Li et al., 2022).

Studies on the role of IT management highlight that artificial intelligence is reshaping leadership and management practices in multiple ways. For instance, research indicates that AI supports digital transformation leadership by creating new roles such as CIOs, data scientists, and AI specialists, while also emphasizing the risks associated with the shortage of such professionals (Gaffley & Pelser, 2021). Similarly, democratization initiatives in large corporations demonstrate how AI can reposition IT from a traditional support function to a central strategic capability, thereby requiring reskilling and fostering new interdisciplinary collaborations (van Giffen & Ludwig, 2023). Other studies show that machine learning–based recommendations are transforming managerial decision-making, increasing efficiency but simultaneously raising concerns about transparency and overreliance on automated systems (Sturm et al., 2023). Overall, AI is driving a shift in leadership and management from primarily soft-skill–oriented roles toward data-driven responsibilities. At the same time, it introduces hybrid professional roles and new collaboration models, although persistent issues of data quality and model accuracy continue to pose significant challenges (Fridman et al., 2023).

An examination of 19 articles reveals that AI has different positive, negative, and transformative effects on each role, but common effects are also possible. Productivity is seen as a common positive impact across nearly all roles. In software roles, the time savings effect is prominent, while in data roles and IT management, process improvements stand out as a positive impact. Negative impacts vary depending on the task. In software-related roles, AI poses a threat of replacing inexperienced workers; in data-oriented roles, it introduces competency barriers and ethical concerns; and in IT management roles, it diminishes transparency. From a transformative perspective, AI integrates software roles and equips them with problem-solving capabilities, assigns responsibilities to data roles, and shapes IT management roles as data-driven leadership. Table 4 summarizes and illustrates these roles and their effects.

Table 4. The three-dimensional impacts of AI on IT roles

Role	Positive Impacts	Negative Impacts	Transformative Impacts
Software	Productivity gains via automation of repetitive coding; support for junior developers' learning (e.g., Copilot, ChatGPT).	Job insecurity for novice developers; risk of overreliance; concerns on reliability and accountability.	Shift from routine coding to oversight, integration, and problem-solving; redefinition of skill requirements.
Data	Acceleration of data analysis; improved modeling (e.g., deep learning in SEM); efficiency gains.	Reduced demand for entry-level analysts; barriers for those lacking advanced technical skills.	Emergence of responsible AI practices; stronger ethical awareness; reshaping expectations of data work.
IT Management	Enhanced decision-making; support for digital transformation; new leadership roles (CIOs, data scientists, AI experts).	Transparency and overreliance concerns in decision-making; risks from lack of AI-skilled professionals.	Transformation of leadership toward data-driven strategies; hybrid professional roles; interdisciplinary work.

RESULTS

Findings from this systematic literature review indicate that AI is significantly impacting a specific set of IT roles over others. The literature has focused more on the impacts on software development, data analytics, and IT management, and less on roles related to IT infrastructure and operations. In terms of sub-roles, the most studied one is its impact on the software development role. The report, prepared by Cisco (2024) with the participation of tech giants like IBM, Google, Intel, and Microsoft, predicts that nearly all IT roles will be impacted by AI, but currently, software development role is experiencing the most significant effect. Although there are not many studies on the ratio of software developers to IT employees, the fact that software developers have the highest ratio among IT employees according to indirect statistical data may be the main motivation for this focus (Bureau of Labor Statistics, 2023).

Findings within the general IT framework, in line with the literature, show that AI has positive, negative and transformative effects on different IT roles. AI has the potential to reduce entry-level employment for software development roles, this result aligns with Johnson (2025) and Chen et al. (2025). The systematic review also shows that it may have a talent barrier-raising effect for data roles and a transparency-reducing effect for management roles. Productivity gains, as noted by sources such as OECD (2024), the addition of new competencies pointed out by Farhan (2023), and the emergence of ethical roles as indicated by Dwivedi et al. (2025) are all consistent with the transformative effects revealed by the systematic review.

This systematic literature review reveals that generative AI has the greatest potential to impact less experienced workforce in software development among IT roles. This also validates the literature emphasizing similar findings. The fact that studies predominantly focus on software development roles and find that these roles are affected by generative AI indicates that future research examining workforce-technology relationships needs to be conducted in a more focused manner based on occupational characteristics. While this study demonstrates through the literature that software development is affected by generative AI, it does not consider whether other roles are impacted by technologies beyond generative AI, such as automation. This study has additional limitations, including its methodological approach, its focus on AI with a specifically defined scope as the sole technology, and its restriction of the systematic review to certain types of publications. The necessity emerges for future studies to be conducted in greater numbers, with more focused approaches in terms of both roles and technologies, and using more empirical methods.

The impact of artificial intelligence on productive IT roles underscores the need for education policymakers to expand existing curricula to include the appropriate use of AI, along with AI model development and training. Given the challenges of creating training programs responsive to rapidly evolving technology, more adaptive and inclusive models must be established to facilitate multiple career transitions for individuals. While AI and other technologies do not currently threaten job displacement for highly skilled roles or physical labor positions, such outcomes remain within the realm of speculation. Technology- and occupation-agnostic, more inclusive strategies are needed.

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Ethics Statement: Ethics committee approval is not required for this study.

Author Contributions Statement: Author contribution rate 100%.

Conflict of Interest: There is no conflict of interest among the authors.

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LEADERSHIP STYLES, EMPLOYEE PERFORMANCE, AND TURNOVER INTENTION: A TWO-MODEL EMPIRICAL ANALYSIS

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Abstract

This study examines how distinct leadership styles, autocratic, transactional, democratic, and transformational, relate to employee performance, and how performance, in turn, associates with turnover intention in organizations operating across Uzbekistan's public and private sectors. Drawing on cross-sectional survey data from 200 employees in government, manufacturing, banking, and service industries, the analysis employed descriptive statistics, Pearson correlations, and multiple regressions to assess these associations. Transformational leadership emerged as the sole style positively linked with employee performance, whereas autocratic, transactional, and democratic forms showed no significant connection. Employee performance displayed a strong inverse relationship with turnover intention, indicating that higher-performing employees tend to express lower intent to leave. The results reveal the continued prevalence of autocratic and transactional practices within Uzbek organizations but underscore the value of transformational leadership in enhancing performance and fostering workforce stability. The study contributes empirical evidence from a transitional economy and offers implications for leadership development, performance management, and future research on leadership–retention dynamics.

Keywords: Leadership styles, employee performance, turnover intention.
Article Type: Research Article.

LİDERLİK TARZLARI, ÇALIŞAN PERFORMANSI VE İŞTEN AYRILMA NİYETİ: İKİ MODELLİ ANALİZ

Atıf/©: Shokhrukh, N., & Aktaş, B. N. (2025). Liderlik tarzlari, çalışan performansı ve işten ayrılma niyeti: İki modelli analiz. *Uluslararası Yönetim Araştırmaları ve Uygulamaları Dergisi, 4*(2), 23-42.

Özet

Bu çalışma, liderlik tarzlarının (otokratik, işlemsel, demokratik ve dönüşümcü) çalışan performansı üzerindeki etkilerini ve devamında çalışan performansının işten ayrılma niyeti üzerindeki etkisini, Özbekistan'da faaliyet gösteren örgütler özelinde incelemektedir. Nicel ve kesitsel bir araştırma deseni benimsenmiş; devlet, imalat, bankacılık ve hizmet sektörlerinde çalışan 200 kişiden yapılandırılmış anketler yoluyla veri toplanmıştır. Değişkenler arasındaki ilişkileri incelemek amacıyla tanımlayıcı istatistikler, Pearson korelasyonu ve çoklu regresyon analizleri uygulanmıştır. Bulgular, incelenen örgütlerde otokratik ve işlemsel liderlik tarzlarının en yaygın olduğunu göstermektedir. Tüm liderlik tarzları arasında yalnızca dönüşümcü liderliğin çalışan performansı üzerinde anlamlı ve pozitif bir etkisi olduğu belirlenmiştir. Otokratik, işlemsel ve demokratik liderlik tarzlarının ise istatistiksel olarak anlamlı bir etkisi bulunamamıştır. Ayrıca, çalışan performansının işten ayrılma niyeti üzerinde güçlü ve negatif bir yordayıcı olduğu saptanmıştır. Çalışma, Özbekistan'da otokratik ve işlemsel liderliğin baskınlığını vurgulamakta ve örgütlerin yüksek performanslı çalışanları elde tutmak ve performansı artırmak amacıyla dönüşümcü liderliği teşvik etmeleri gerektiğinin altını çizmektedir. Teorik, uygulamaya yönelik ve gelecekteki araştırmalara ilişkin çıkarımlar tartışılmıştır.

Anahtar Kelimeler: Liderlik tarzları, çalışan performansı, işten ayrılma niyeti.
Makale Türü: Araştırma Makalesi.

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1. INTRODUCTION

Leadership remains one of the most decisive forces shaping organizational outcomes, influencing how individuals interpret goals, engage in work, and sustain commitment. While global research has produced extensive evidence on leadership's influence on performance and retention, its effectiveness is not uniform across contexts (Avolio et al., 2009; Asrar-ul-Haq & Kuchinke, 2016). Much of what is known about leadership has been derived from Western organizational settings, where participative norms, low power distance, and open communication are taken for granted. These assumptions, however, do not always align with the realities of transitional economies, where managerial control, institutional hierarchy, and collective social expectations remain deeply embedded. Uzbekistan represents one such context in which organizational leadership continues to operate within authority-centered traditions inherited from the Soviet administrative model (Veliu et al., 2017).

This historical and institutional background makes Uzbekistan a compelling environment in which to examine how leadership functions and what forms are most effective. In many Uzbek organizations, leadership practices continue to reflect command-and-control structures, even as new market-oriented management philosophies emerge. Autocratic and transactional leadership often dominate, while democratic and transformational approaches appear less institutionalized. Whether such dominance enhances or constrains employee outcomes remains an unresolved empirical question with direct implications for organizational development in the region.

Previous studies show that leadership style is associated with both employee performance and turnover intention, often through mechanisms of motivation, satisfaction, and commitment (Puni et al., 2016; Praditya, 2022). Transformational leadership is frequently linked to higher engagement and stronger performance (Roz, 2019; Rony et al., 2023), whereas autocratic and transactional styles are often connected to lower morale and greater intention to leave (Mbah & Ikemefuna, 2011; Kalambayi et al., 2021). Yet, research from transitional and post-socialist economies indicates that even directive or hierarchical leadership can sometimes maintain efficiency in structured environments that rely on authority and compliance (Anyango, 2015; Gopal & Chowdhury, 2014; Wang & Guan, 2018). These mixed findings suggest that leadership effectiveness cannot be assumed to follow a single pattern; it must be understood in relation to local institutional and cultural conditions.

This study investigates how four leadership styles, autocratic, transactional, democratic, and transformational, relate to employee performance, and how performance, in turn, associates with turnover intention within organizations operating in Uzbekistan. Employing a quantitative, cross-sectional design, the study draws on data from employees in government, manufacturing, banking, and service sectors. The analysis proceeds in two stages: first, examining the relationships between leadership styles and performance; and second, testing how performance relates to turnover intention.

The contribution of this study is twofold. Theoretically, it refines the scope of Full Range Leadership Theory (Avolio & Bass, 2004; Bass & Riggio, 2006) by examining its propositions in a high power-distance and control-oriented environment. In doing so, it clarifies how contextual and institutional characteristics shape the relational meaning of leadership behaviors and their linkages to employee outcomes. Practically, it provides evidence on which leadership styles are most prevalent and effective in Uzbekistan's evolving organizational landscape, thereby offering guidance for leaders seeking to balance authority with empowerment. Together, these contributions respond to a central question for leadership research: how established theories of influence perform when applied within the distinctive structural and cultural conditions of transitional economies.

2. CONCEPTUAL FRAMEWORK

The four leadership forms considered in this study, autocratic, democratic, transactional, and transformational, capture a spectrum that extends from command orientation to participative and visionary influence. Autocratic leadership, first identified by Lewin et al. (1939), reflects concentrated authority and unilateral decision-making. Later analyses confirm that autocratic leaders rely on formal power and rarely delegate discretion to subordinates (Gastil, 1994; Rosing et al., 2022). While this structure can preserve order in highly regulated or crisis settings, it often restricts communication and suppresses initiative. Democratic leadership, in contrast, disperses authority through consultation and collective problem-solving. Originating from the same early typology (Lewin et al., 1939), this style positions employees as active participants in organizational decisions. Contemporary interpretations emphasize its participatory nature, leaders solicit input, integrate feedback, and foster a cooperative climate that encourages ownership and trust (Northouse, 2021; Rosing et al., 2022).

Transactional leadership, conceptualized by Burns (1978) and refined through subsequent empirical work, is grounded in exchange logic. Leaders clarify expectations, monitor compliance, and reward performance based on predefined criteria (Aarons, 2006; Judge & Piccolo, 2004). This approach tends to stabilize operations and secure short-term results in structured environments, yet it rarely generates commitment beyond contractual obligation. Transformational leadership, introduced by Burns (1978) and expanded by Bass (1985), represents a qualitatively different form of influence. It relies on articulating vision, stimulating intellectual engagement, and addressing individual needs to elevate followers' motivation. A substantial body of research associate's transformational behaviors with higher performance and satisfaction across diverse organizational settings (Aarons, 2006; Bass & Riggio, 2006).

Beyond leadership itself, two outcome constructs define the present inquiry. Turnover intention refers to an employee's conscious willingness to leave the organization, a variable consistently recognized as the most direct predictor of actual turnover behavior (Tang et al., 2022). Prior studies show that turnover intention is shaped by perceived fairness, stress, job satisfaction, and commitment (Chin & Hung, 2013; Lee et al., 2018; Lee et al., 2020; Norizan et al., 2023). Understanding its antecedents is therefore crucial for managing organizational stability. Employee performance captures how effectively individuals execute assigned tasks in both quality and quantity terms (Triansyah et al., 2023; Aryata & Marendra, 2023). Performance is influenced not only by skill and effort but also by interpersonal dynamics and organizational culture (Ma et al., 2013; Sartika et al., 2021).

These constructs delineate the conceptual map guiding this study. Leadership style provides the behavioral context within which employees interpret expectations and allocate effort; performance represents the observable outcome of that interaction; and turnover intention reflects its longer-term attitudinal consequence. This framework enables an examination of how differing leadership approaches correspond with performance and how, in turn, performance aligns with employees' intention to remain or depart, issues particularly salient in hierarchical and transitional organizational systems such as those found in Uzbekistan.

3. HYPOTHESES DEVELOPMENT

3.1. Leadership Styles and Employee Performance

Leadership is a fundamental factor influencing employee motivation, satisfaction, and organizational growth (Azhar, 2004; Fry, 2003; Paarlberg & Lavigna, 2010). Among the major approaches, democratic, transformational, transactional, and autocratic leadership each embody distinct assumptions about authority, participation, and reward systems.

Democratic leadership emphasizes participation and shared decision-making. By involving employees in problem-solving and encouraging open dialogue, democratic leaders cultivate belonging and self-efficacy, which correspond with higher motivation and task ownership (Agarwal, 2020; Andoh & Ghansah, 2019; Kalambayi et al., 2021; Suryadinata, 2023). Open communication and delegation further reinforce responsibility and trust, conditions associated with stronger performance and collaboration (Ahmad et al., 2014; Cooper, 2015; Koohang et al., 2017).

Transformational leadership extends beyond participation to address deeper psychological engagement. Through articulating vision, offering individualized consideration, and stimulating intellectual growth, transformational leaders inspire employees to transcend immediate self-interest, often translating into enhanced performance and satisfaction (Anwar et al., 2023; Hadi, 2018; Khan et al., 2020; Roz, 2019; Rony et al., 2023). Research across diverse contexts finds that transformational and transactional behaviors combined can balance inspiration with structure, improving organizational effectiveness (Alharbi & Aljounaidi, 2021; Asrar-ul-Haq & Kuchinke, 2016).

Transactional leadership, grounded in clear expectations and contingent rewards, is frequently associated with stable task performance (Alharbi & Aljounaidi, 2021; Judge & Piccolo, 2004). Its emphasis on structure and accountability can be beneficial in routine or compliance-driven environments. However, studies also indicate that its reliance on external reinforcement limits creativity and intrinsic motivation in dynamic settings requiring adaptation and innovation (Baig et al., 2019; Khan & Nawaz, 2016; Ohemeng et al., 2018; Omonona et al., 2019).

Autocratic leadership, defined by centralized control and unilateral decision-making, tends to suppress initiative and reduce satisfaction, thereby constraining performance (Anyango, 2015; Dolly & Nonyelum, 2018; Gopal & Chowdhury, 2014; Luque et al., 2008). While such authority can produce short-term efficiency in contexts demanding strict coordination or compliance, prolonged reliance on coercive control often diminishes morale and elevates turnover risk (Iqbal et al., 2015; Nwokocha & Iheriohanma, 2015; Wang & Guan, 2018).

Taken together, empirical findings indicate that leadership styles fostering participation, inspiration, and personal growth are more consistently associated with positive performance outcomes than those grounded in command or transactional control. These observations inform the present study’s first set of hypotheses:

Hypothesis 1: Autocratic leadership style is negatively associated with employee performance.

Hypothesis 2: Transactional leadership style is positively associated with employee performance.

Hypothesis 3: Democratic leadership style is positively associated with employee performance.

Hypothesis 4: Transformational leadership style is positively associated with employee performance.

3.2. Employee Performance and Turnover Intention

Employee performance constitutes a central determinant of organizational effectiveness, reflecting how efficiently individuals contribute to collective goals and sustain long-term productivity (Dessler, 2013; Rachman, 2017; Robbins & Coulter, 2012). High-performing employees typically demonstrate stronger job satisfaction and deeper organizational commitment, which correspond with lower turnover intention (Al-Ali et al., 2019; Dahlan et al., 2023; Han et al., 2024; Iqbal et al., 2020; Widyani et al., 2019). This relationship is frequently reinforced through job satisfaction, which functions as a psychological link between performance outcomes and the decision to remain. Satisfaction, when supported by effective leadership and equitable workplace culture, strengthens attachment to the organization and reduces withdrawal tendencies (Alias et al., 2018; Suswati, 2020; Yusupova et al., 2024).

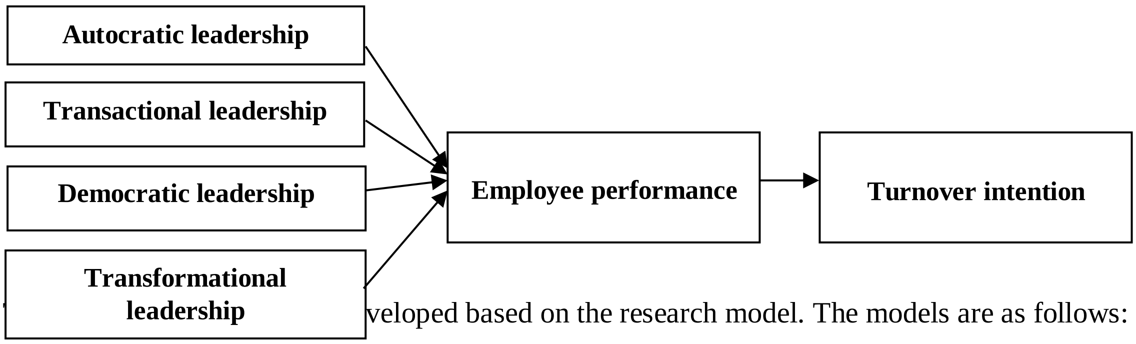
However, the association between performance and turnover intention is not uniform. Exceptional employees may still seek external opportunities when recognition, compensation, or advancement are perceived as inadequate (Ariyabuddhiphongs & Khan, 2017; Park & Min, 2020). Similarly, persistent stressors or perceptions of unfair treatment can erode satisfaction, weakening the stabilizing effect of high performance and increasing the likelihood of departure (Applebaum, 2010; Lo et al., 2017; Villanueva & Djurkovic, 2009). These contingencies highlight that performance alone does not guarantee retention; contextual and motivational factors determine whether strong performers remain committed or disengage.

Drawing on these evidences, higher levels of performance are expected to correspond with lower turnover intention. Therefore, we hypothesize:

Hypothesis 5: Employee performance is negatively associated with turnover intention.

A conceptual model has been developed to illustrate the relationships among leadership styles, employee performance, and turnover intention. As depicted in Figure 1, it provides the theoretical foundation for the subsequent empirical analysis.

Figure 1. Hypothesized Model



veloped based on the research model. The models are as follows:

Model 1: $EP_i = \alpha_0 + \alpha_1 ALS_i + \alpha_2 TRLS_i + \alpha_3 DLS_i + \alpha_4 TLS_i + \varepsilon_i$

Where, EP_i—employee performance in organization i, ALS_i—autocratic leadership in organization i, $TRLS_i$—transactional leadership in organization i, DLS_i—democratic leadership in organization i, TLS_i—transformational leadership in organization i, α_0—intercept (constant), α_1—α_4—are coefficients, ε_i—error term. Thus, the first model examines how various leadership styles, autocratic, transactional, democratic, and transformational, affect employee performance, with performance serving as the dependent variable.

Model 2: $TI_i = \beta 0 + \beta 1 EP_i + \varepsilon_i$

Where, TI_i—turnover intention in organization i, EP_i—employee performance in organization i, β_0 —intercept (constant), β_1—coefficients, ε_i—error term. The second model explores the link between employee performance on turnover intention.

The use of two separate regression models in this study is intentional and theoretically guided. The sequential structure reflects the underlying framework in which leadership styles are conceptually associated with employee performance, and employee performance is in turn related to turnover intention. Modeling these associations separately enables a focused examination of each relationship while avoiding assumptions of temporal order or untested mediation. This stepwise design aligns with the study's objectives and is supported by methodological recommendations that advocate separate estimation when indirect effects are not being formally tested (Baron & Kenny, 1986; Hayes, 2018).

4. METHODOLOGY

4.1. Research Design

The study employed a quantitative, cross-sectional design to examine the associations among leadership styles, employee performance, and turnover intention within organizations operating in Uzbekistan. This design was selected to capture employees' perceptions across multiple sectors and to identify relational patterns rather than causal effects. Data were gathered through a structured survey, enabling standardized measurement and statistical comparison across variables.

4.2. Sample and Data Collection

Participants were drawn from organizations in the government, manufacturing, banking, and service sectors. A total of 200 valid responses were obtained using a purposive sampling approach targeting full-time employees with at least one year of organizational tenure. Participation was voluntary and anonymous to reduce social desirability bias. Respondents represented a range of organizational levels and demographic backgrounds, providing a heterogeneous but contextually relevant sample for examining leadership–performance dynamics in transitional economies. The survey instrument was first developed in English, translated into Uzbek, and back-translated to ensure conceptual and linguistic equivalence following Brislin's (1970) procedure.

Ethical approval for this study was granted by the Beykoz University Research Ethics Committee on 13.05.2025 (Approval No. E-45152895-299-2500008937). Participation was entirely voluntary, and informed consent was obtained before respondents completed the survey. All participants were assured that their responses would remain confidential and be used exclusively for academic research.

The demographic profile of the sample (N = 200) demonstrates a balanced representation across key organizational and personal characteristics, presented in Table 1. Respondents were evenly distributed among government, manufacturing, banking, and service sectors, each comprising 25% of the total sample, thus minimizing sectoral bias and supporting generalizability across organizational types. In terms of marital status, 47% of participants were married, 32% unmarried, and 21% divorced, indicating substantial diversity in personal backgrounds. Educational attainment was notably high: the majority (83%) held a higher education degree, while only 15.5% had secondary education and 1.5% vocational education. This aligns with the study's context and increases the likelihood of informed survey responses. The average age of respondents was 33 years (SD = 7.59), with ages ranging from 20 to 51 years. This suggests a workforce primarily composed of early- to mid-career professionals. Correspondingly, the mean level of professional experience was 5.16 years (SD = 2.85), with a range from 1 to 15 years. Collectively, these demographic results provide a robust foundation for analyzing the impact of leadership styles on employee outcomes in a relatively young and well-educated workforce.

4.3. Measurements

All constructs were measured using established scales adapted to the local context while retaining the original conceptual structure. Respondents rated each statement on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Leadership styles scale: Four leadership styles, autocratic, democratic, transactional, and transformational, were assessed. Each has 5 items. The transformational and transactional dimensions were derived from the Multifactor Leadership Questionnaire (Avolio & Bass, 2004; Bass & Riggio, 2006). Given contextual constraints, shorter validated subsets of items were used to preserve internal consistency while minimizing respondent fatigue. Autocratic and democratic leadership were measured with items adapted from established instruments in prior research (Lewin et al., 1939; Northouse, 2021). These items captured decision-making centralization, participation, and communication patterns consistent with each style's theoretical core.

Employee performance scale: Employee performance was measured using a 5-items task-performance scale reflecting efficiency, reliability, and goal attainment (Dessler, 2013; Robbins & Coulter, 2012; Rachman, 2017). This self-report measure focuses on employee's perceived contribution to their organization's objectives.

Turnover intention scale: Turnover intention is a single construct without a sub-dimension and was measured through 5-items scale, assessing the respondent's stated likelihood or willingness to leave their organization (Tang et al., 2022). Items were selected from previously validated turnover intention scales and adapted linguistically for local comprehensibility.

4.4. Data Analysis

Descriptive statistics, Pearson's correlation, and multiple regression analyses were used to examine the hypothesized associations. Two models were estimated. Model 1 tested the relationships between leadership styles and employee performance. Model 2 examined the association between employee performance and turnover intention. To maintain interpretive clarity and avoid statistical suppression, leadership styles were not treated as control variables in the second model. All analyses were conducted using SPSS version 26.

5. RESULTS

5.1. Descriptive Statistics

Table 2 presents the descriptive statistics for the main study variables. Across all leadership styles, mean scores were moderate, with autocratic and transactional leadership demonstrating the highest average levels (M = 3.49 and M = 3.44, respectively), followed by transformational (M = 3.12) and democratic leadership (M = 3.06). This distribution suggests a prevailing influence of more directive leadership approaches within the sampled organizations, while participative and transformational behaviors, though present, were less dominant. Employee performance (M = 3.41, SD = 1.09) and turnover intention (M = 3.34, SD = 1.13) also reflected moderate central tendencies, with both variables exhibiting substantial variability (range: 1.8–5.0 for EP; 1.8–5.0 for ETI). All variables displayed a wide spread, covering most of the Likert scale, which indicates heterogeneity in both perceived leadership practices and individual work outcomes among respondents. These results establish a context of considerable diversity in leadership experiences and outcomes, laying a sound empirical foundation for subsequent reliability, correlation, and regression analyses.

The results indicate that all scale variables are approximately symmetric, with skewness values ranging from –0.54 to 0.14. Skewness values below ±2 and kurtosis values below ±7 are generally considered indicative of normality in social science research (Tabachnick & Fidell, 2013; West et al., 1995). In this study, all variables fall well within these limits, suggesting no serious floor or ceiling effects. Kurtosis values (between –1.63 and –1.23) indicate slightly platykurtic distributions, which are not problematic for parametric analyses such as correlation and regression.

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	25th %ile	Median	75th %ile	Max	Skewness	Kurtosis
Autocratic Leadership	3.49	0.98	1.6	2.40	3.80	4.20	5.0	-0.538	-1.232
Transactional Leadership	3.44	1.04	1.2	2.40	3.80	4.40	5.0	-0.467	-1.228
Democratic Leadership	3.06	1.05	1.8	2.00	3.30	4.00	5.0	0.135	-1.522
Transformational Leadership	3.12	1.15	1.8	1.80	3.40	4.40	4.8	0.102	-1.632
Employee Performance	3.41	1.09	1.8	2.20	3.80	4.20	5.0	-0.219	-1.383
Turnover Intention	3.34	1.13	1.8	2.20	3.40	4.20	5.0	-0.129	-1.447

5.2. Leadership Styles in Selected Organizations

The descriptive analysis of leadership style items indicates that autocratic leadership (Mean = 3.49) and transactional leadership (Mean = 3.44) are the most prevalent leadership styles perceived by employees in the sampled organizations in Uzbekistan. Transformational (Mean = 3.12) and democratic (Mean = 3.06) leadership styles are less commonly reported. The relatively higher means for autocratic and transactional styles suggest that Uzbek organizations may continue to rely on more traditional, hierarchical leadership approaches, possibly reflecting the influence of historical, cultural, or institutional factors specific to the region. These findings are consistent across all items within each style, confirming a pattern in which authority, rules, and structured rewards remain central to workplace leadership. The lower mean scores for transformational and democratic leadership styles highlight opportunities for organizations in Uzbekistan to develop more participative and inspirational leadership practices, which have been linked to higher employee performance in international studies. Item-level descriptive statistics are presented in Table 3.

Table 3. Item-Level Descriptive Statistics for Leadership Styles

Style	Item	Mean	SD
Autocratic leadership	ALS1	3.50	1.55
	ALS2	3.63	1.26
	ALS3	3.40	1.25
	ALS4	3.38	1.14

Style	Item	Mean	SD
	ALS5	3.52	1.05
Transactional leadership	TRLS1	3.58	1.35
	TRLS2	3.55	1.22
	TRLS3	3.44	1.18
	TRLS4	3.56	1.34
	TRLS5	3.06	1.34
Democratic leadership	DLS1	3.01	1.58
	DLS2	3.21	1.25
	DLS3	3.07	1.01
	DLS4	3.06	1.20
	DLS5	2.94	1.25
Transformational leadership	TLS1	2.98	1.58
	TLS2	2.94	1.00
	TLS3	3.31	1.05
	TLS4	3.13	1.19
	TLS5	3.25	1.35

5.3. Reliability and Validity Tests

First, to assess potential common-method variance, Harman's single-factor test was conducted using all measurement items. The unrotated factor solution yielded six factors with eigenvalues greater than 1, explaining 79.12 % of the total variance. The first factor accounted for 28.30 % of the variance, well below the 50 % threshold, indicating that common-method bias was unlikely to distort the observed associations (Podsakoff et al., 2003).

The appropriateness of the dataset for factor analysis was assessed through the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity, as outlined in Table 4. The KMO score reached 0.796, reflecting a satisfactory level of sampling adequacy and indicating that the correlation patterns are suitably compact to produce distinct and dependable factors (Kaiser, 1974; Hair et al., 2019). Additionally, Bartlett's Test yielded a highly significant result (χ^2 = 8076.372, df = 435, $p < 0.001$), reinforcing that the correlation matrix deviates significantly from an identity matrix and that the variables exhibit sufficient intercorrelation to justify factor analysis. Collectively, these statistical outcomes provide robust support for moving forward with exploratory factor analysis, as the data meet widely accepted criteria for methodological soundness (Field, 2018; Tabachnick & Fidell, 2013).

Table 4. KMO and Bartlett's Test

Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.796
Bartlett's Test of Sphericity (Approx. Chi-Square)	8076.372
df	435
Sig. (p-value)	.000

Table 5 shows the exploratory factor analysis factor (EFA), yielded a six-factor solution, with each set of items, autocratic leadership (ALS), transactional leadership (TRLS), democratic leadership (DLS), transformational leadership (TLS), employee performance (EP), and turnover intention (TI), loading primarily on their respective factors. This result provides strong empirical support for the construct validity of the scales used in the study. Most items exhibited very high loadings (generally above 0.80) on their respective factors, indicating that each scale measured a distinct and coherent underlying construct. The six-factor solution accounted for approximately 78.8% of the total variance, a robust result for social science research and further confirmation of the appropriateness of the measurement structure.

Although EFA indicated clear separation among the six constructs, with each item set loading strongly onto its intended factor, the observed composite correlation between employee performance and turnover intention was extremely high and negative (see Table 7). This discrepancy is likely attributable to response patterns or sample-specific factors, rather than conceptual or measurement overlap. Thus, the measurement model is empirically sound, but the sample data exhibited unusually strong inverse association between these two outcomes.

Table 5. Factor Analysis

Items	Factors						Eigenvalues	Variance Explained
	1	2	3	4	5	6		
TI1	.920							
TI 2	.916							
TI 3	.827						7.04	24.3%
TI 4	.916							
TI 5	.895							
EP1		.825						
EP2		.922						
EP3		.841					4.39	15.1%
EP4		.899						
EP5		.834						
TLS1			.945					
TLS2			.921					
TLS3			.911				3.50	12.1%
TLS4			.944					
TLS5			.903					
DLS1				.939				
DLS2				.902				
DLS3				.765			3.42	11.8%
DLS4				.838				
DLS5				.685				
TRLS1					.874			
TRLS2					.867			
TRLS3					.849		3.19	11.0%
TRLS4					.874			
TRLS5					.545			
ALS1						.909		
ALS2						.911		
ALS3						.602	1.31	4.5%
ALS4						.894		
ALS5						.686		
							Total	78.8%

The internal consistency of each scale was evaluated using Cronbach's alpha (see Table 6). All multi-item scales demonstrated strong reliability, with Cronbach's alpha values well above the conventional threshold of 0.70. Specifically, the transformational leadership, employee performance, and turnover intention scales exhibited excellent reliability (α = 0.96, 0.92, and 0.94, respectively), while the remaining leadership scales demonstrated good reliability (α = 0.84–0.89). These results confirm that the survey instruments used in this study are both consistent and reliable for measuring the targeted constructs, thereby supporting the robustness of subsequent analyses.

Table 6. Reliability Test

Scale	Number of Items	Cronbach's Alpha
Autocratic Leadership	5	0.84
Transactional Leadership	5	0.87
Democratic Leadership	5	0.89
Transformational Leadership	5	0.96
Employee Performance	5	0.92
Turnover Intention	5	0.94

5.4. Correlation Test

Table 7 presents the Pearson correlations among study variables. As shown, most associations are weak to moderate in magnitude. Transformational leadership shows a small positive correlation with employee performance ($r = .19$, $p < .05$), while employee performance and turnover intention are strongly and negatively related ($r = –.98$, $p < .01$). Other correlations are relatively low and non-significant, indicating limited multicollinearity among constructs.

Table 7. Correlation Matrix

	1	2	3	4	5	6
1. Autocratic Leadership	—					
2. Transactional Leadership	.23**	—				
3. Democratic Leadership	–.04	.00	—			
4. Transformational Leadership	–.13	–.10	.08	—		
5. Employee Performance	–.01	–.06	.11	.19*	—	
6. Turnover Intention	.00	.05	–.09	–.18	–.98**	—

p < .05*, *p < .01.

5.5. Hypotheses Tests

Regression analyses were conducted to test the study hypotheses regarding the impact of leadership styles on employee performance (see Table 8) and, subsequently, the effect of employee performance on turnover intention (see Table 9). Model 1 tested hypotheses from H1 to H4, and Model 2 is used to test the H5.

Table 8. Model 1 - Predicting Employee Performance from Leadership Styles

Predictor	β	SE	t	p	95% CI
(Constant)	2.63	0.48	5.53	<0.001	[1.69, 3.57]
Autocratic Leadership	0.03	0.08	0.42	0.677	[–0.12, 0.19]
Transactional Leadership	–0.05	0.08	–0.64	0.525	[–0.20, 0.10]
Democratic Leadership	0.10	0.07	1.36	0.176	[–0.04, 0.24]
Transformational Leadership	0.17*	0.07	2.50	0.013	[0.04, 0.30]
$R^2 = 0.046$; Adjusted $R^2 = 0.026$; $N = 200$					

Predictor	β	SE	t	p	95% CI
Notes: $F(4,195) = 2.34$; *$p < .05$ (model is marginally significant overall)					

In Model 1, only transformational leadership demonstrated a statistically significant positive effect on employee performance ($\beta = 0.17$, $p = 0.013$). Autocratic, transactional, and democratic leadership styles did not exhibit significant relationships with employee performance. The overall model explained 4.6% of the variance in employee performance ($R^2 = 0.046$). These findings underscore the importance of transformational leadership behaviors in enhancing performance outcomes, consistent with established theoretical expectations.

Table 9. Model 2 - Predicting Turnover Intention from Employee Performance and Controls

Predictor	B	SE	β	t	p	VIF
(Constant)	6.103	0.058		105.13	< .001	
Employee Performance	–1.008	0.016	–.975	–62.08	< .001	1.000
$R^2 = .951$, Adj $R^2 = .951$, Std. Error = .249, Durbin–Watson = 2.139						

Model 2 tested the association between employee performance and turnover intention without including leadership controls. The results showed a very strong and statistically significant negative relationship between the two constructs ($\beta = –.98$, $p < .001$). The model accounted for 95.1 % of the variance in turnover intention ($R^2 = .951$), indicating that employees who reported higher performance also reported markedly lower intentions to leave their organizations. Regression diagnostics confirmed that multicollinearity was absent (VIF = 1.00, Tolerance = 1.00), residuals were independent (Durbin–Watson = 2.14), and no influential cases were detected (Cook's D < 1). These results provide strong support for H5. The standardized coefficient ($\beta = –.975$) mirrors the bivariate correlation ($r = –.98$), as expected in a single-predictor model, confirming that the strong inverse relationship is substantive rather than a statistical artifact.

DISCUSSION

A substantial body of research has explored how leadership shapes employee performance and, in turn, influences turnover intention. The dominant view holds that leadership style affects performance by shaping motivation, commitment, and perceived fairness, which subsequently influence employees' intentions to stay or leave (Liphadzi et al., 2015). The present study confirms this general theoretical logic but also refines it by showing that, among four examined styles, only transformational leadership emerged as a significant positive correlate of employee performance.

This finding reinforces extensive evidence that transformational leaders enhance intrinsic motivation, strengthen identification with organizational goals, and cultivate commitment that translates into higher performance outcomes (Judge & Piccolo, 2004; Khan et al., 2020; Asrar-ul-Haq & Kuchinke, 2016; Roz, 2019; Rony et al., 2023; Widjaja et al., 2020). The absence of significant effects for autocratic and transactional leadership parallels earlier research showing that these styles are effective mainly in highly routinized or hierarchical environments but can suppress creativity and engagement elsewhere (Anyango, 2015; Gopal & Chowdhury, 2014; Omonona et al., 2019; Baig et al., 2019). The non-significance of democratic leadership, although unexpected, may reflect contextual contingencies in Uzbekistan's organizational landscape, where decision authority and cultural expectations of hierarchy may dilute participative mechanisms even when formally present (Andoh & Ghansah, 2019; Kalambayi et al., 2021).

Beyond leadership effects, the study found an extremely strong inverse relationship between employee performance and turnover intention. High-performing employees were markedly less inclined to leave their organizations. While such magnitude is uncommon in behavioral data, validity checks confirmed that it reflects a substantive association rather than a measurement artifact. The pattern aligns with evidence that high performers typically experience greater job satisfaction and stronger affective commitment, reducing their propensity to quit (Al-Ali et al., 2019; Han et al., 2024; Widyani et al., 2019). Within Uzbekistan's emerging economy context, this may also indicate limited alternative employment opportunities for high achievers or strong relational bonds between supervisors and competent subordinates, both of which reinforce retention.

The results underscore that transformational leadership remains the most adaptive style for enhancing employee performance in diverse and evolving organizational environments, while employee performance itself functions as a stabilizing mechanism against turnover.

Theoretical Contribution

This study interprets its findings through the complementary perspectives of Full Range Leadership Theory (FRLT) and Social Exchange Theory (SET), using both as explanatory lenses. The pattern that only transformational leadership shows a significant positive association with employee performance aligns conceptually with FRLT's view that inspirational and visionary behaviors foster stronger motivational engagement (Avolio & Bass, 2004; Bass & Avolio, 1994). Within the Uzbek context, this correspondence illustrates how leadership behaviors emphasizing vision, intellectual stimulation, and individualized support are associated with higher performance, while transactional, democratic, and autocratic approaches show no such pattern. These results do not confirm the full FRLT hierarchy but instead delineate its boundaries, suggesting that transformational elements of the framework appear salient even where authority structures remain hierarchical.

Moreover, SET provides a complementary interpretive frame for understanding the strong inverse association between employee performance and turnover intention. Classical SET reasoning posits that perceived reciprocity and fair exchange strengthen employees' attachment to their organizations (Blau, 1964; Cropanzano & Mitchell, 2005). Although perceptions of exchange quality were not directly measured here, the observed pattern is coherent with SET logic. Employees who perform well are also those who, in many contexts, perceive or expect reciprocal recognition, thereby expressing lower intentions to leave. This correspondence demonstrates theoretical resonance rather than empirical proof of exchange dynamics.

Viewed together, FRLT and SET help to locate the study's empirical regularities within broader theoretical conversations. Transformational behaviors appear congruent with performance enhancement in a transitional economy, and the performance–turnover linkage follows the exchange logic of retention. By interpreting rather than testing these frameworks, the study clarifies the scope conditions under which their core ideas remain meaningful and highlights avenues for future research that model the mediating and contextual mechanisms more directly (Avolio & Bass, 2004; Bass & Avolio, 1994; Blau, 1964; Cropanzano & Mitchell, 2005).

Practical Implications

In the workplaces reflected by this study, leadership is not simply a matter of authority but of atmosphere, the tone a leader sets in how people see purpose, voice, and recognition. The data shows that transformational leadership stands out as the form most closely associated with stronger employee performance. In practice, this means that when leaders share an aspirational vision, attend to individual growth, and communicate genuine belief in their teams, performance tends to rise in ways that numbers alone cannot capture (Anyango, 2015; Widjaja et al., 2020). Yet democratic leadership, widely praised in management literature for boosting motivation, appeared neutral here, perhaps since participation can feel hollow when cultural or institutional hierarchies quietly constrain it. Transactional leadership, with its focus on clear expectations and contingent rewards, remains useful as a framework for accountability, but its full potential seems to unfold only when woven together with transformational habits that speak to meaning and belonging (Alharbi & Aljounaidi, 2021; Ohemeng et al., 2018).

The findings also remind us that autocratic leadership has a narrow and situational role. In moments of crisis, decisiveness may be necessary, but sustained command can drain creativity and morale, eroding the very performance it seeks to enforce (Iqbal et al., 2015; Nwokocha & Iheriohanma, 2015). What endures longer than compliance is commitment, and commitment grows where people feel heard. A climate of dialogue, openness, and shared responsibility builds the psychological safety that allows employees to contribute more fully (Iqbal et al., 2015).

The unusually strong inverse association between performance and turnover intention points toward a simple, human truth, that is people rarely leave when their effort is seen and valued. Organizations that recognize high performance, provide developmental feedback, and offer visible paths for growth convert performance into attachment rather than exhaustion (Kadiresan et al., 2015; Haque, 2020). Recognition, in this sense, is a gesture and a mechanism of exchange, precisely what Social Exchange Theory describes.

Finally, work stress, cultural expectations, and labor-market competition all shape how leadership and performance translate into loyalty (Hidayat, 2023; Skelton et al., 2019). Investing in employees' psychological capital and emotional intelligence deepens resilience and helps sustain engagement even when external conditions are volatile (Maamari & Saheb, 2018; Ohemeng et al., 2018).

Future Research

The current body of literature underscores the need for further studies that explore the dynamic interplay of leadership style, cultural context, and psychological capital in influencing employee performance. Although substantial evidence affirms that transformational and democratic leadership styles are associated with positive performance outcomes, future research should aim to delineate the specific conditions under which each leadership style is most effective. There is also a call for more longitudinal studies that track changes in employee performance over time as influenced by leadership behaviors, especially in the face of rapid technological and organizational changes (Asrar-ul-Haq & Kuchinke, 2016; Ohemeng et al., 2018). Additionally, Scholars and practitioners alike would benefit from studies that compare leadership effectiveness across different industries, examining how factors such as industry structure, employee demographics, and cultural norms interact with leadership styles to shape performance (Baig et al., 2019; Khan & Nawaz, 2016). While the evidence largely supports a negative relationship between employee performance and turnover intention, the variability in effect sizes and the occasional observation of curvilinear relationships indicate that additional moderating and mediating variables need further exploration. Future research should address the mechanisms by which performance influences turnover intentions in specific contexts and investigate the potential bidirectional effects between organizational performance and turnover (Wang & Sun, 2020). For instance, studies employing cross-lagged panel designs could elucidate whether improved organizational performance further reinforces employees' commitment and retention, or whether high turnover intention among key performers might in turn detract from overall organizational performance. There is also a need to examine the role of individual differences, in terms of employee personality, career aspirations, and market conditions, in moderating the performance–turnover link (Alam & Asim, 2019; Kim et al., 2017).

Limitations

This study has several limitations that should be considered when interpreting the results. First, the cross-sectional design restricts the ability to make causal inferences and may not capture the dynamic nature of leadership and employee outcomes over time. Second, the study sample was limited to organizations in Uzbekistan, and results may not generalize to other contexts without further validation. Third, while the adapted scales showed good construct validity, further research is needed to ensure full cultural adaptation and psychometric robustness in the local context. Finally, the study did not account for other organizational or individual factors that may influence employee performance and turnover, such as compensation, organizational support, or external job opportunities.

CONCLUSION

This study contributes to the expanding literature on leadership and organizational behavior by empirically assessing the relationship between leadership styles, employee performance, and turnover intention in the context of Uzbek organizations. The results underscore the distinct effectiveness of transformational leadership in driving employee performance, while the other leadership styles examined showed no statistically significant influence in this setting. Additionally, the observed strong negative link between performance and turnover intention supports the notion that high-performing employees are substantially less likely to consider leaving their organizations. These findings emphasize the importance for organizations in transitional economies to cultivate transformational leadership capabilities and to implement targeted retention strategies that align with the expectations of high-performing employees. In sum, the study contributes to both theoretical understanding and practical applications of leadership in shaping employee outcomes, offering a valuable starting point for future research across varied cultural and organizational landscapes.

STATEMENTS/DECLARATIONS

Ethics Statement: Permission for this study was obtained from the Ethics Committee of Beykoz University Scientific Research and Publication Ethics Committee with the decision number 1 at the meeting dated 13/05/2025 and numbered 12 of the relevant board. In case of detection of a contrary situation, Journal of International Management Research and Applications has no responsibility and all responsibility belongs to the author(s) of the study.

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