Uluslararası Yönetim Araştırmaları ve Uygulamaları Dergisi
Journal of International Management Research and Applications
Cilt/Volume: 4 | Sayı/Issue: 2 | Aralık/December 2025

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

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First Received/ Makale İlk Gönderim Tarihi: *18.09.2025*
Accepted/ Makale Kabul Tarihi: *03.11.2025*

Citation/©: Mayuk, M. K., (2025). The information technology workforce in the AI era: A systematic review of roles and skills. *Journal of International Management Research and Applications*, *4*(2), 1-22.

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:

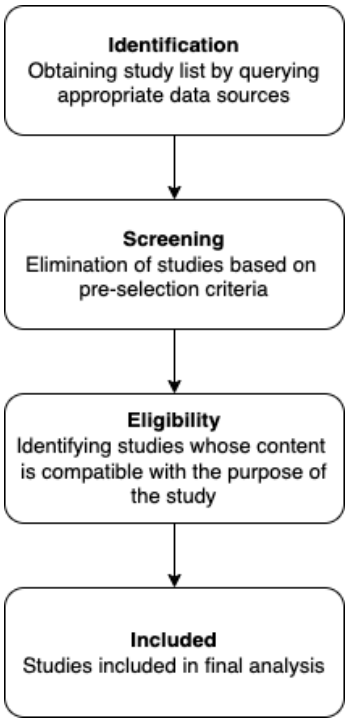
i. Which specific IT roles are addressed in the existing body of research?
ii. What impacts (positive, negative, transformative) of AI on the IT workforce are revealed in the studies and in what dimensions?

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

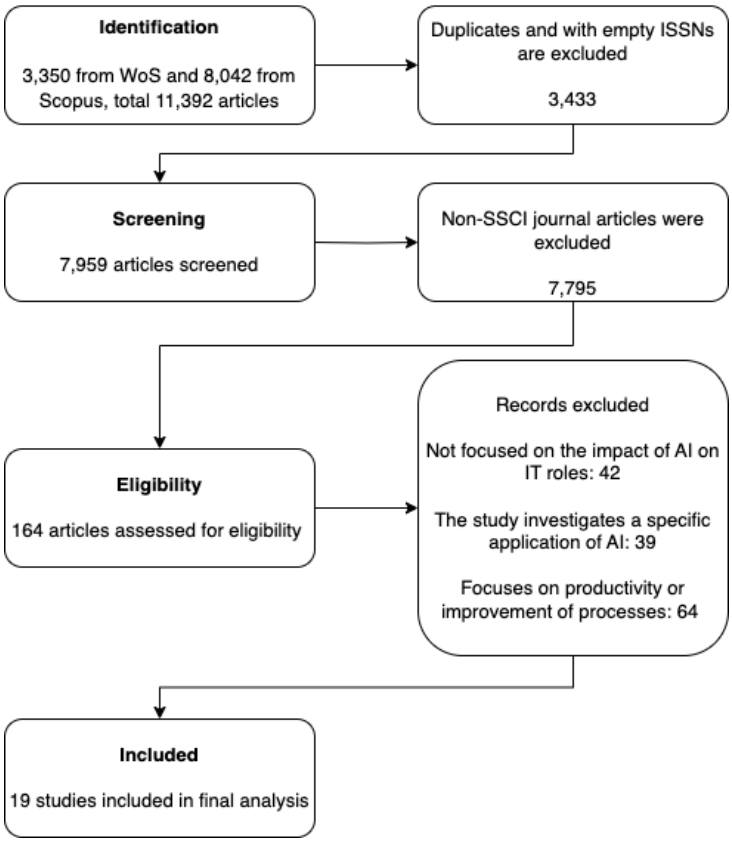
AND (LIMIT-TO(DOCTYPE, "ar"))

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



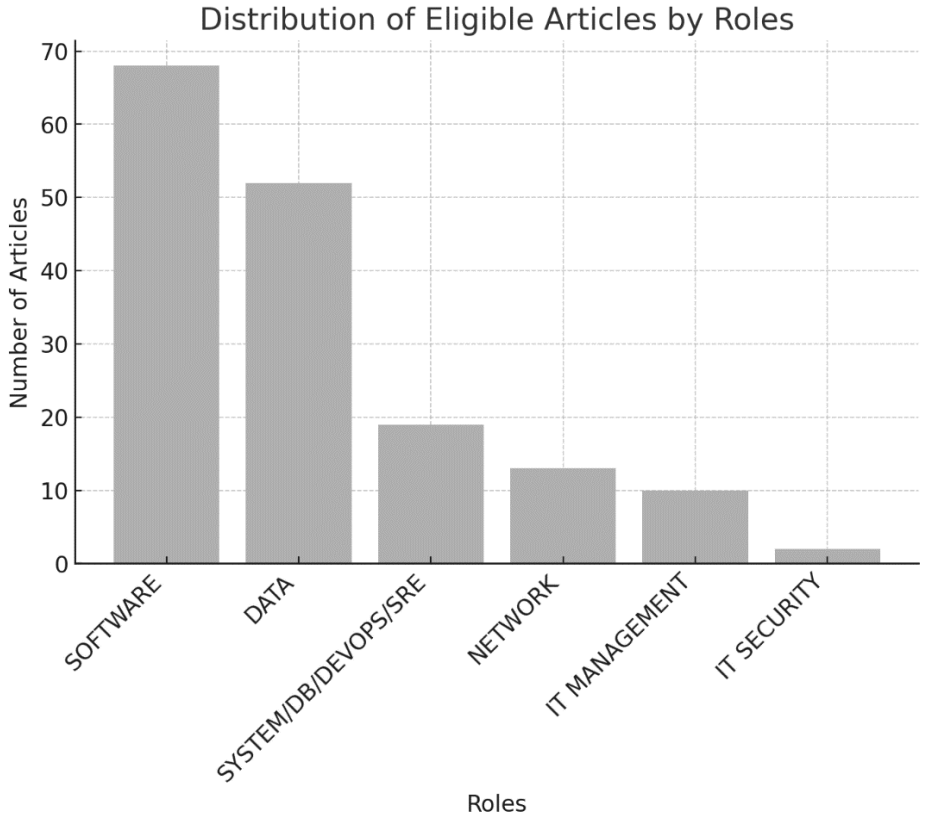
The database search yielded 11,392 articles, of which 3,350 were retrieved from Web of Science and 8,042 from Scopus. After removing duplicates and records without ISSN information, 7,959 articles remained. Restricting the dataset to articles published in SSCI-indexed journals resulted in a final set 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.

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

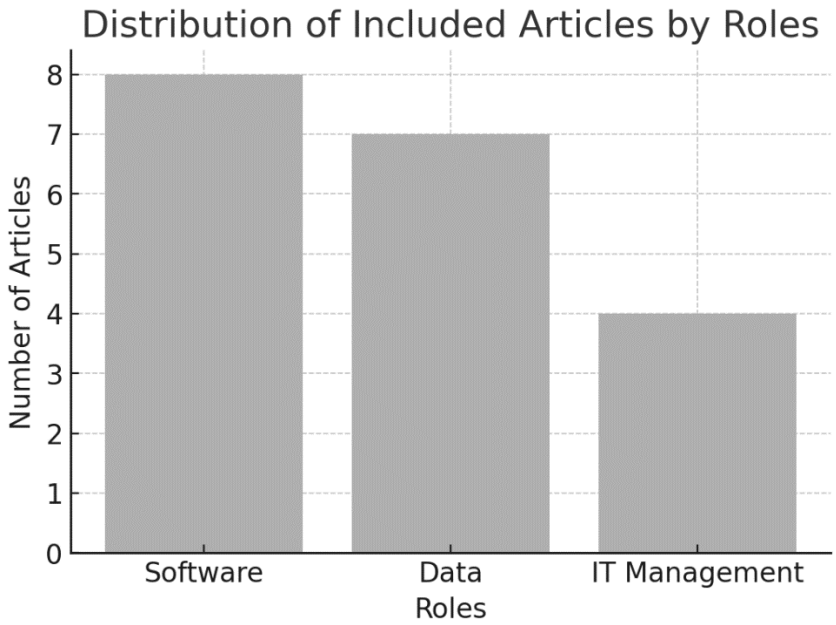
The findings can be presented in two stages: descriptive and research focused. The descriptive findings report the frequency and number of 164 eligible and 19 included studies. With respect to the research topic, a total of 19 articles were identified to determine the roles examined and the extent of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

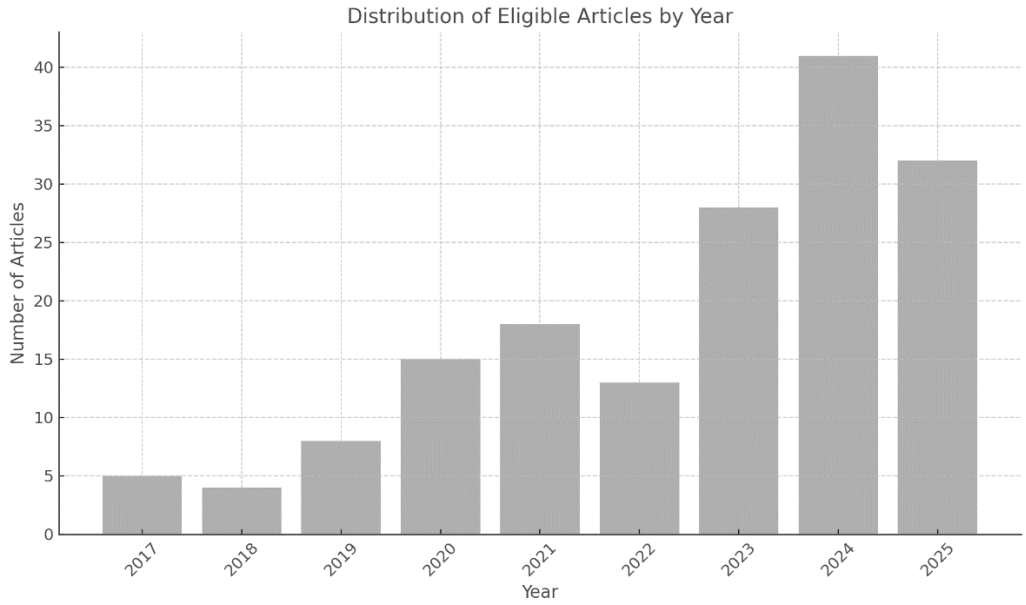
Figure 4. Distribution of included articles by roles

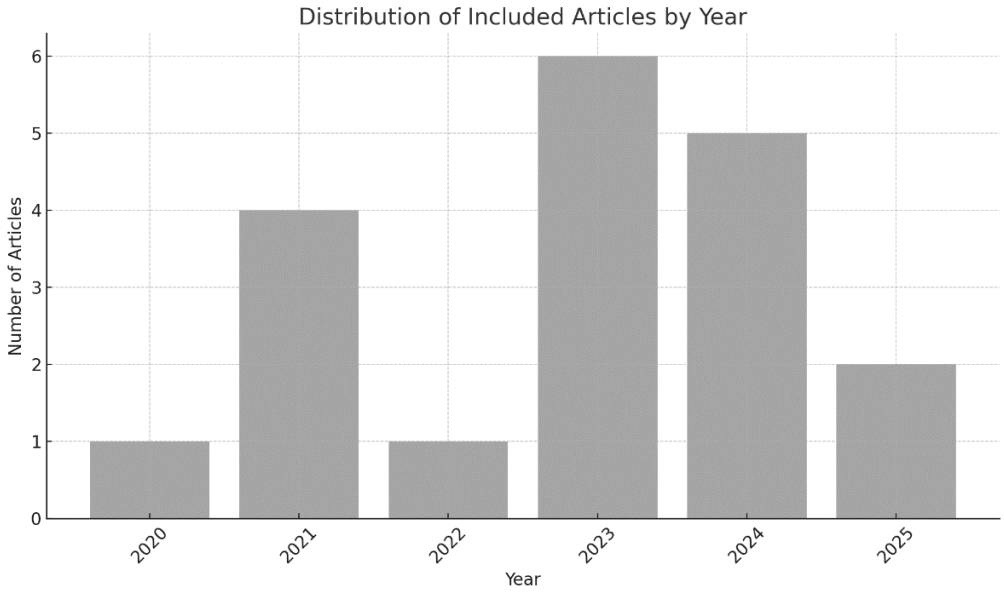


Role-based numbers indicate that areas related to IT infrastructure and engineering are understudied and are not sufficiently included in the IT roles that will be affected by AI. When the most frequently studied role category—software—is considered, 68 of the 164 eligible articles address software-related 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.

STATEMENTS/DECLARATIONS

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.

Funding: This research received no external funding.

Data Availability Statement: The author confirms that all data generated or analyzed during this study are based on the literature.

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