Artificial Intelligence in Administrative Functions: A 2026 Systematic Literature Review of Adoption, Applications, Efficiency, Decision-Making, and Human–AI Collaboration

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ABSTRACT

Artificial intelligence (AI) is changing how organizations operate in both public and private sectors. Although many studies have explored AI in administrative functions, the findings are spread across different disciplines, making it difficult to see the overall picture. A systematic review is therefore needed to bring together recent evidence and identify future research directions.

This study conducted a systematic literature review (SLR) following the PRISMA 2020 guidelines. Relevant studies were identified and screened using the Web of Science (WoS) and Scopus database based on predefined inclusion and exclusion criteria. In total, 99 articles were included in the final analysis and examined using thematic analysis. Five main themes were identified. The first, AI Adoption and Digital Transformation in Administrative Functions, shows how AI supports organizational modernization and change. The second, Applications of AI in Administrative Processes, focuses on automation and improvement of routine administrative tasks. The third, Administrative Efficiency and Productivity, highlights how AI improves operational performance through automation and process optimization. The fourth, Decision-Making Quality and Organizational Effectiveness, is the most prominent theme, showing AI's strong role in supporting data-driven decisions and improving organizational performance. The fifth, Staff Performance and Human–AI Collaboration, explains how AI enhances employee capabilities and changes how humans and AI work together. Overall, the findings show that AI plays an important role in transforming administrative systems, improving efficiency, and supporting workforce development. However, challenges remain in areas such as governance, transparency, and organizational readiness. This review integrates fragmented evidence into a coherent framework and highlights key implications for future research, management practice, and policy development on responsible AI adoption in administrative settings.

Keywords: Artificial Intelligence (AI); Administrative Processes; Digital Transformation; Decision-Making Quality; Organisational Effectiveness

INTRODUCTION

Artificial Intelligence (AI) has become an important technology in modern organizations, changing how administrative activities are carried out, information is managed, and decisions are made. AI includes technologies such as machine learning (ML), natural language processing (NLP), expert systems, and robotic process automation (RPA), which allow machines to perform tasks that traditionally require human intelligence (Russell & Norvig, 2021). As organizations continue their digital transformation, AI is increasingly being used to automate routine activities, process large amounts of information, improve workflows, and support daily operations. This growing adoption has created increasing interest in understanding how AI can influence organizational efficiency and performance.

In administrative settings, AI can be applied to activities such as information processing, document management, workflow automation, resource allocation, employee administration, service delivery, and

operational monitoring. By reducing repetitive tasks and processing information more quickly, AI may help organizations improve administrative efficiency and productivity. Previous research has identified efficiency improvement, data processing, resource optimization, and service delivery as important benefits of AI adoption, particularly in organizational and public-sector contexts (Madan & Ashok, 2023; Zuiderwijk et al., 2021). Recent research also suggests that AI can improve efficiency through automation, predictive analysis, and better resource allocation. However, these benefits depend on factors such as organizational readiness, employee capabilities, ethical considerations, and effective governance.

AI is also increasingly being used to support organizational decision-making. AI systems can analyse large and complex datasets, identify patterns, generate predictions, and provide information that helps managers evaluate alternatives. Davenport and Ronanki (2018) highlighted the use of AI in business processes, customer and employee engagement, and cognitive insights, demonstrating its potential beyond simple task automation. In public administration, AI has also been associated with decision support and improved decision-making (Zuiderwijk et al., 2021). At the same time, the use of AI in decision-making raises concerns about transparency, accountability, fairness, privacy, and human oversight. Therefore, the impact of AI cannot be understood only in terms of its technological capabilities or potential efficiency gains.

The implementation of AI in administrative environments also presents several challenges. These include data privacy and security, algorithmic bias, transparency, accountability, ethical issues, technological limitations, organizational readiness, and employee resistance to changes in established work practices. Madan and Ashok (2023) highlighted concerns related to fairness, transparency, privacy, and human rights in AI adoption and diffusion within public administration. Similarly, Zuiderwijk et al. (2021) identified technological, organizational, managerial, skills-related, ethical, legal, social, and economic challenges. These findings suggest that the benefits of AI depend greatly on how the technology is implemented, governed, and integrated with human work.

Although considerable research has examined AI adoption, the existing evidence remains fragmented across sectors and research areas. Previous reviews have mainly focused on public administration, public governance, healthcare, education, and other specific contexts. For example, Zuiderwijk et al. (2021) examined AI in public governance and identified efficiency, performance, data processing, and decision-making as potential benefits, while also highlighting governance and ethical concerns. Madan and Ashok (2023) examined AI adoption in public administration, with emphasis on organizational, technological, and environmental factors. While these studies provide valuable foundations, less attention has been given to administrative functions across different organizational settings.

Another gap is that administrative efficiency and decision-making are often studied separately. Research on efficiency generally focuses on automation, productivity, workflow improvement, and resource optimization, whereas decision-making studies tend to emphasize predictive analytics, data-driven insights, and decision support. Examining these areas together is important because they are closely connected. Improved information processing and workflow automation may support faster and better decisions, while effective decision-making can contribute to better resource allocation and administrative performance.

The rapid development of AI further highlights the need for an updated synthesis of current evidence. Earlier reviews identified the need for more empirical research, stronger theoretical foundations, multidisciplinary studies, and greater understanding of the organizational and governance implications of AI (Zuiderwijk et al., 2021). As AI applications continue to expand, recent studies may provide new evidence that is not fully reflected in earlier reviews. A systematic review of recent research can therefore provide a clearer picture of how AI is currently being used in administrative functions and its reported outcomes and challenges.

Accordingly, this study aims to systematically review and synthesize existing literature on the impact of AI on administrative efficiency and decision-making. It focuses on identifying key AI applications, assessing their contribution to administrative performance, examining their influence on decision-making processes, and exploring the challenges associated with AI adoption. The study provides a consolidated overview of current knowledge, highlights emerging trends and research gaps, and offers practical insights for organizations seeking to implement AI effectively.

The remainder of this paper is structured as follows. The next section describes the research methodology used in conducting the systematic literature review, including the search strategy, inclusion and exclusion criteria, and data analysis methods. This is followed by the results section, which presents the key findings from the selected studies. The discussion section interprets these findings in relation to existing theories and their practical implications. Finally, the conclusion highlights the study's main contributions, limitations, and suggestions for future research.

METHODOLOGY

Review Protocol

This study uses the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure a clear, systematic, and reproducible review process. PRISMA is a well-established framework used across many fields, including management, information systems, and healthcare, to improve transparency in how studies are selected and reported (Page et al., 2021).

PRISMA is appropriate for this study because research on AI in administrative efficiency and decision-making is broad and rapidly expanding. It provides a structured way to document how studies are identified, screened, and included, helping to reduce bias and improve reliability (Moher et al., 2009; Page et al., 2021). Compared to traditional review methods, it ensures greater rigor through a more standardized process (Snyder, 2019). The review followed four main steps: defining research questions, searching for relevant studies, assessing their quality, and extracting and analyzing data. These steps ensure that the findings are based on a systematic and well-organized review of the literature on AI in administration and decision-making.

The formulation of research questions

Research questions are an essential part of a systematic literature review (SLR) because they define its direction, scope, and focus. They guide all key stages of the review, including keyword selection, search strategy, database choice, study screening, eligibility criteria, and data extraction (Kitchenham & Charters, 2007). Clear research questions help keep the review focused and reduce irrelevant studies, while also improving transparency and replicability (Snyder, 2019). In addition, research questions are used to develop search terms and Boolean strings, set inclusion and exclusion criteria, and assess study relevance during screening. They also guide what information is extracted and analyzed from the selected studies (Page et al., 2021). For this study, the research questions were developed based on the objective of examining AI adoption and its impact in administrative settings. The focus is on AI adoption trends, administrative efficiency, decision-making, and staff performance, supported by prior literature on AI and organizational performance (Dwivedi et al., 2021; Russell & Norvig, 2021).

Based on the objectives of the study, the following research questions were formulated:

1. What AI adoption patterns and administrative applications are reported in studies published in 2026?
2. What administrative outcomes, including efficiency, decision-making, and staff performance, are reported in studies of AI applications published in 2026?

These questions provide a clear framework for identifying, evaluating, and synthesizing existing evidence on AI in administrative contexts.

Systematic Searching Strategy

A systematic searching strategy is a structured method used in a systematic literature review (SLR) to identify, screen, and select relevant studies. It follows clear and predefined steps to ensure that the review is comprehensive, transparent, and reproducible. The main aim is to identify relevant studies while reducing the risk of missing important evidence or introducing bias (Kitchenham & Charters, 2007; Page et al., 2021).

This approach improves the quality of the review by using clear keywords, selected databases, and defined inclusion and exclusion criteria. The search terms in this study focused on Artificial Intelligence (AI), administrative efficiency, workflow automation, and operational efficiency. Decision-making and staff performance were examined during screening, eligibility assessment, and data extraction rather than being used as mandatory search terms. This approach maintained the focus on AI applications in administrative functions while allowing relevant studies to be identified (Snyder, 2019).

Following the PRISMA 2020 guidelines, the search process in this study involved three stages: identification, screening, and eligibility (Page et al., 2021).

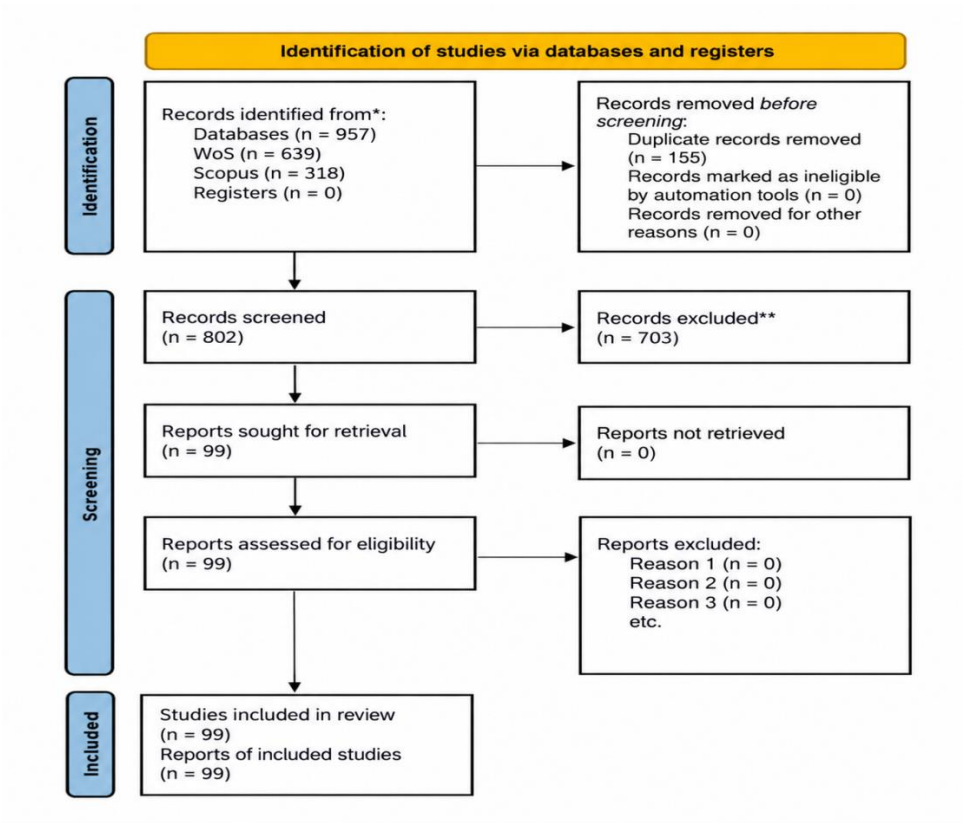
Identification

The identification stage aimed to locate studies related to the impact of Artificial Intelligence (AI) on administrative efficiency and decision-making. The search keywords were developed based on the research objectives and research questions (Kitchenham & Charters, 2007; Page et al., 2021). Key terms included artificial intelligence, machine learning, deep learning, administrative efficiency, workflow automation, and operational efficiency. To ensure a comprehensive search, synonyms and related terms were included and combined using Boolean operators such as AND and OR. Phrase searching and truncation symbols (*) were also used to improve the accuracy and coverage of the search results.

The literature search was conducted using Web of Science (WoS) and Scopus. In WoS, the Topic Search (TS) function was used to search titles, abstracts, author keywords, and Keywords Plus. The Scopus search used the TITLE-ABS-KEY field to search titles, abstracts, and author keywords.

The WoS search string was *TS = (("artificial intelligence" OR AI OR "machine learning" OR "deep learning") AND ("administrative efficien" OR "workflow automation" OR "operational efficien"))***, while the Scopus search string was adapted accordingly. The searches identified 639 records from WoS and 318 from Scopus, giving 957 records in total. The records were then combined and prepared for screening and eligibility assessment. The overall study selection process is presented in the PRISMA flow diagram.

Figure 1 PRISMA 2020 flow diagram for new systematic reviews



Screening

This systematic literature review was restricted to studies published in 2026 to provide a focused synthesis of recent evidence on artificial intelligence (AI) in administrative functions. It examined AI adoption and applications, administrative efficiency, decision-making, and human–AI collaboration. Therefore, the review presents a snapshot of recent research rather than an analysis of developments over time.

The screening process followed the research questions and predefined eligibility criteria. Studies were included if they examined AI adoption or applications in administrative functions and addressed administrative processes, efficiency, productivity, decision-making, or staff performance. Studies focusing solely on technical AI development without clear relevance to administrative functions were excluded.

The initial search identified 957 records from Web of Science (WoS) (639) and Scopus (318). After removing 155 duplicates, 802 records remained for title and abstract screening. Of these, 703 were excluded as irrelevant, leaving 99 reports for full-text assessment. All 99 reports were retrieved and found eligible, resulting in 99 studies being included in the final review. The selection process is illustrated in the PRISMA flow diagram (Figure 1).

The restriction to 2026 publications is a limitation, as it prevents comparisons across years and limits understanding of how AI adoption in administrative functions has evolved. Therefore, the findings represent the available literature identified for 2026 and should not be generalised to the entire research field. Future reviews could cover a longer publication period to identify changes and emerging trends over time.

Eligibility

Eligibility assessment was the third stage of the systematic review process, conducted after the screening and retrieval stages. At this stage, the full-text reports were examined to determine whether they provided sufficient and relevant evidence to address the review objective and research questions. While the screening stage focused mainly on titles and abstracts, the eligibility assessment involved a detailed review of the complete articles to evaluate their suitability for inclusion in the study (Page et al., 2021).

The assessment focused on identifying studies that examined the impact of Artificial Intelligence (AI) on administrative efficiency and decision-making. To ensure a thorough evaluation, the methodology, findings, discussion, and conclusion sections of each article were reviewed. This process helped identify studies that provided relevant empirical or theoretical evidence on AI adoption in administrative functions, its applications in different organizational contexts, and its effects on efficiency, decision-making, and staff performance.

A total of 99 full-text reports were assessed for eligibility. No studies were excluded at this stage because all retrieved reports were found to be relevant to the review objective and research questions. Therefore, all 99 studies were retained for the final synthesis. The results of the eligibility assessment are presented in the PRISMA 2020 flow diagram and served as the foundation for the subsequent data extraction, analysis, and synthesis of findings (Page et al., 2021).

Quality appraisal

The selected studies were assessed to evaluate their methodological quality and reporting standards. The quality appraisal criteria were adapted from Abouzahra et al. (2020) and covered six aspects: clarity of research objectives, usefulness of the study, methodological transparency, clarity of key concepts, comparison with similar studies, and discussion of limitations.

Each criterion was scored as Yes (1.0), Partly (0.5), or No (0), giving a maximum score of 6.0. Studies scoring at least 3.0 were retained for the review. However, the total score was not treated as the sole indicator of study quality. The individual criteria were also considered to identify methodological strengths and limitations that could influence confidence in the reported findings.

A total of 99 studies were assessed, and all met the minimum quality threshold and were retained for the final synthesis. Differences in methodological reporting, comparison with previous research, and discussion of limitations were considered when interpreting the findings. The quality appraisal therefore supported a more critical synthesis by distinguishing well-supported findings from those requiring cautious interpretation.

As the review included studies with potentially different research designs, the appraisal results should be interpreted in relation to the information reported by each study. The assessment provided a consistent framework for reviewing study quality, although it did not replace design-specific evaluation of methodological rigour.

Data extraction and analysis

Data extraction was conducted after the screening, eligibility, and quality appraisal stages. The purpose was to systematically collect relevant information from the selected studies to answer the research questions. A structured extraction approach was used to ensure consistency, accuracy, and relevance (Kitchenham & Charters, 2007).

The principal author extracted key information mainly from the results and discussion sections of each study, as these contained the most relevant findings. Additional details were taken from other sections when necessary. To improve reliability, the extracted data were reviewed and validated by at least one co-author.

The data were then analysed using thematic analysis, a common method for identifying patterns across qualitative findings (Braun & Clarke, 2006). This method was chosen because it allows the synthesis of studies with different designs and contexts.

The analysis followed six phases: familiarisation with the data, coding, searching for themes, reviewing themes, defining and naming themes, and producing the final report (Braun & Clarke, 2006). Through this process, key patterns related to AI adoption and its impact on administrative functions were identified.

Five main themes emerged from the analysis: (1) AI adoption and digital transformation in administration, (2) applications of AI in administrative processes, (3) impact on administrative efficiency and productivity, (4) impact on decision-making quality and organisational effectiveness, and (5) impact on staff performance and human–AI collaboration.

These themes were used to synthesise findings from the 99 included studies and to address the research questions of the review.

RESULTS AND DISCUSSION

Study's background

The final review comprised 99 articles, all of which were published in 2026. Consistent with systematic review methodology, the selection of this publication period was aligned with the review objective of synthesising current evidence rather than providing a historical overview of the topic (Snyder, 2019; Xiao & Watson, 2019). The year 2026 was chosen because it provided a substantial body of relevant studies examining the adoption and impact of Artificial Intelligence (AI) in organizational and administrative settings. The high volume of publications reflects the growing importance of AI as a strategic tool for enhancing administrative efficiency, decision-making, and organizational performance. Focusing on studies published in 2026 enabled the review to capture the most recent developments, applications, and emerging trends in this rapidly evolving field, thereby providing a contemporary understanding of the current state of knowledge.

The included studies show a broad global distribution, reflecting the widespread interest in AI in administrative contexts. Most studies were conducted in Asia (Heliani et al., 2026; Yang et al., 2026; Morshed & Khrais, 2026; Zhang et al., 2026; Sun et al., 2026; Li et al., 2026; Yue et al., 2026; Alwreikat et al., 2026; Saihi, Jose et al., 2026; Han et al., 2026; Alsadoun & Alateeg, 2026).

Europe also contributed a notable number of studies (Akusta, 2026; Silva, 2026; Safiullina & Safiullin, 2026; Jabbouri et al., 2026; Labib et al., 2026; Tsirantonaki, 2026; Gontarek & Cunha, 2026; Stein, 2026; Pluskota et al., 2026; Bitetti et al., 2026; Flogie et al., 2026), followed by North America (Ahn & Kim, 2026; Sezgin & Boch, 2026; Li et al., 2026). Fewer studies were from South America (Espinoza et al., 2026), while a small number represented Oceania, particularly Australia (Mohammed & Guillet, 2026).

The reviewed studies covered a wide range of sectors, showing the broad application of AI in administrative functions. These included healthcare (Demir et al., 2026; El Sarraj et al., 2026; Mohammed et al., 2026; Santos et al., 2026), manufacturing and operations management (Fri et al., 2026; Kulkarni & Khanzode, 2026), supply chain and procurement (Cui et al., 2026; Liu et al., 2026), and public administration (Thanh & Cong, 2026; Wang et al., 2026).

Other contexts included auditing and compliance (Sun, 2026; Varma & Sharma, 2026), legal and contract management (Ali et al., 2026), entrepreneurship and business services (Antoniuk & Ivens, 2026), cybersecurity (Gazzola et al., 2026), and law enforcement intelligence (Dolan, 2026).

Most of the reviewed studies adopted quantitative methods as the primary research design. These studies commonly used techniques such as machine learning models, predictive analytics, structural equation modelling, optimization methods, simulation, and statistical analysis to assess AI performance and organizational outcomes (Demir et al., 2026; Kulkarni & Khanzode, 2026; Sun, 2026; Thanh & Cong, 2026; Varma & Sharma, 2026).

Qualitative approaches were also widely applied, including interviews, case studies, thematic analysis, and focus groups. These were mainly used to explore AI adoption, organizational readiness, and user perceptions (Antoniuk & Ivens, 2026; El Sarraj et al., 2026; Nevi et al., 2026; Yavetz & Nakash, 2026).

In addition, some studies developed conceptual frameworks or conducted systematic reviews to strengthen theoretical understanding and identify future research directions (Fri et al., 2026; Santos et al., 2026; Wang et al., 2026).

Overall, the publication and geographical patterns indicate that research on AI-enabled decision support and organizational transformation is gaining momentum, particularly in Asia and Europe. The concentration of studies in these regions suggests strong institutional and industrial interest in AI implementation. However, comparatively limited representation from Africa and Oceania highlights opportunities for future research in underexplored contexts. Additionally, while many studies focus on improving efficiency, productivity, and operational performance, fewer investigations address long-term governance, ethical considerations, sustainability implications, and human-centered AI adoption. These gaps suggest important avenues for future research and theory development.

Quality appraisal

To ensure the quality and relevance of the included studies, a quality appraisal was conducted using six criteria adapted from Abouzahra et al. (2020): (QA1) clarity of objectives, (QA2) relevance of the study, (QA3) methodological rigor, (QA4) clarity of concepts, (QA5) comparison with related studies, and (QA6) discussion of limitations. Each criterion was scored as Yes (1), Partly (0.5), or No (0), with a maximum total score of 6.

Studies scoring at least 3.0 (50%) were included to balance quality and inclusiveness (Kitchenham & Charters, 2007; Pussegoda et al., 2017). All 99 studies met this requirement, with scores ranging from 3.5 to 6.0 and an average of 4.98, indicating generally acceptable quality. All studies clearly presented their objectives, relevance, and key concepts (QA1, QA2, and QA4). Most also met QA3, although some lacked sufficient methodological details. The main weaknesses were in QA5 and QA6, as many studies had limited comparisons with previous research and discussions of their limitations.

These weaknesses were considered when interpreting the findings. Limited methodological details made it difficult to assess the reliability of some results, while the lack of comparisons and discussions of limitations

made it harder to determine whether the findings were consistent and applicable across different organisational settings. Therefore, the findings were interpreted carefully, considering the quality of each study.

Overall, the quality appraisal supported the thematic analysis by identifying the strengths and weaknesses of the selected studies. Although all 99 studies met the minimum quality threshold, their evidence was not equally strong. The appraisal highlighted the need for clearer research methods, better comparisons with previous studies, and more detailed discussions of limitations in future research. This reflects the importance of critically evaluating evidence in systematic literature reviews (Snyder, 2019).

Table 1
Quality appraisal results.

Study	QA1	QA2	QA3	QA4	QA5	QA6	Total Marks
Espinoza et al. (2026) - South America	Y	Y	Y	Y	Y	P	5.5
Heliani et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Yang et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Morshed & Khrais (2026) - Asia	Y	Y	Y	Y	Y	N	5
Zhang et al. (2026) - Asia	Y	Y	P	Y	P	N	4
Sun et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Li et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Saavedra et al. (2026) - South America	Y	Y	Y	Y	P	N	4.5
Yue et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Akusta (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Irgang et al. (2026) - Europe	Y	Y	Y	Y	N	N	4
Alwreikat et al. (2026) - Asia	Y	Y	Y	Y	Y	N	5
Saihi (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Sezgin & Boch (2026) - North America	Y	Y	P	Y	N	N	3.5
Jose et al. (2026) - Asia	Y	Y	Y	Y	N	N	4
Silva (2026) - Europe	Y	Y	P	Y	N	N	3.5
Safiullina & Safiullin (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Ahn & Kim (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Wang, Zhang & Li (2026) - Asia	Y	Y	Y	Y	P	Y	5.5
Dosumu et al. (2026)	Y	Y	Y	Y	Y	N	5
Han et al. (2026) - Asia	Y	Y	Y	Y	Y	Y	6
Mohammed & Guillet (2026) - Oceania	Y	Y	Y	Y	P	N	4.5
Cabanos, Le & Ghassemi (2026) - North America	Y	Y	Y	Y	Y	N	5
Alsadoun & Alateeg (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Mohamad et al. (2026) - Netherlands	Y	Y	Y	Y	P	N	4.5
Jabbouri et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Xing & Zhang (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Alsaadi et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Jeyasheeli et al. (2026) - Asia	Y	Y	Y	Y	Y	N	5
Labib et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Wang (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Nguyen & Pham (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Goyal et al. (2026) - Asia	Y	Y	P	Y	P	Y	5
Baske et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Li et al. (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Quadras et al. (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Keswani (2026) - Asia	Y	Y	Y	Y	P	Y	5.5

Tsirantonaki (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Gontarek & Cunha (2026) - Europe	Y	Y	Y	Y	P	P	5
Ahmad et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Shahzad et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Petsavas & Ioakimidis (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Alajmi (2026) - Asia	Y	Y	Y	Y	P	Y	5.5
Liu (2026) - Asia	Y	Y	Y	Y	P	P	5

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Table 1 (*continued*)

Study	QA1	QA2	QA3	QA4	QA5	QA6	Total Marks
Raimi (2026) - Asia	Y	Y	Y	Y	Y	P	5.5
Stein (2026) - Europe	Y	Y	Y	Y	P	P	5
Pluskota et al. (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Buonocore et al. (2026) - Europe	Y	Y	P	Y	P	Y	5
Quinello & Costa (2026) - South America	Y	Y	Y	Y	Y	Y	6
Al-Ansi et al. (2026) - Asia	Y	Y	Y	Y	Y	Y	6
Gramifar et al. (2026) - North America	Y	Y	Y	Y	Y	Y	6
Dinh et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Jeyaram et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Ibrahim et al. (2026) - Africa	Y	Y	Y	Y	P	P	5
Kwasafo et al. (2026) - Africa	Y	Y	Y	Y	Y	P	5.5
Biancone et al. (2026) - Europe	Y	Y	Y	Y	P	P	5
Bitetti et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Ivancevic & Radojicic (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Liu, Li & Xu (2026) - Asia	Y	Y	Y	Y	Y	P	5.5
Saha, Bose & Alanazi (2026) - Asia	Y	Y	Y	Y	Y	P	5.5
Murphy, Weinstein, Guyton & Porter (2026) - North America	Y	Y	P	Y	P	P	4.5
Pan & Xie (2026) - Asia	Y	Y	Y	Y	Y	P	5.5
Yang (2026) - Asia	Y	Y	Y	Y	Y	P	5.5
Sereewatthanawut et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Ergün (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Wamba-Taguimdje & Kamdjoug (2026) - Europe	Y	Y	Y	Y	P	P	5
Aladiyan (2026) - Asia	Y	Y	Y	Y	Y	N	5
Shiralkar et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Del Barone et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Touzani et al. (2026) - Africa	Y	Y	Y	Y	P	P	5
Flogie et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Pasi et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Ratshalingwa & Civilcharran (2026) - Africa	Y	Y	Y	Y	P	N	4.5
Mhlanga (2026) - Africa	Y	Y	P	Y	P	Y	5
Lambert, Laskovaia, Garanina & Bogatyreva (2026) - Europe	Y	Y	Y	Y	P	P	5
Crofford et al. (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Oliveira et al. (2026) - South America	Y	Y	Y	Y	P	Y	5.5
Buhmann et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Sardi & Modarelli (2026) - Europe	Y	Y	Y	Y	P	N	4.5

Gosho & Mpundu (2026) - Africa	Y	Y	Y	Y	P	P	5
Zuo et al. (2026) - Asia	Y	Y	Y	Y	P	P	5
Fri et al. (2026) - Africa	Y	Y	Y	Y	P	Y	5.5
Kulkarni & Khanzode (2026) - Asia	Y	Y	Y	Y	P	P	5
Wang, Yin & Hu (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Yavetz & Nakash (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Liu et al. (2026) - Asia	Y	Y	Y	Y	P	N	4.5

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Table 1 (*continued*)

Study	QA1	QA2	QA3	QA4	QA5	QA6	Total Marks
Cui, Yu & Li (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Demir, Ayik & Ozbilen (2026) - Europe	Y	Y	Y	Y	Y	P	5.5
El Sarraj, Holt & Bradley (2026) - Europe	Y	Y	Y	Y	P	P	5
Sun (2026) - Asia	Y	Y	Y	Y	P	P	5
Santos et al. (2026) - South America	Y	Y	Y	Y	P	N	4.5
Mohammed et al. (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Nevi et al. (2026) - Europe	Y	Y	Y	Y	P	N	4.5
Antoniuk & Ivens (2026) - Europe	Y	Y	Y	Y	P	Y	5.5
Dolan (2026) - North America	Y	Y	Y	Y	P	Y	5.5
Thanh & Cong (2026) - Asia	Y	Y	Y	Y	P	P	5
Gazzola et al. (2026) - Europe	Y	Y	Y	Y	Y	P	5.5
Varma & Sharma (2026) - Asia	Y	Y	Y	Y	P	N	4.5
Ali, Ali & Jafri (2026) - Asia	Y	Y	Y	Y	P	P	5

Yes (Y), Partly (P), No (N)

The themes

The thematic analysis of the selected studies identified five main themes reflecting the trends, applications, and impact of Artificial Intelligence (AI) in administrative functions. The analysis followed a systematic process of coding, categorisation, and synthesis based on Braun and Clarke (2006). These themes provide a structured understanding of how AI is adopted and applied in organisations.

The five themes were: (1) AI adoption and digital transformation in administrative functions, (2) applications of AI in administrative processes, (3) impact on administrative efficiency and productivity, (4) impact on decision-making quality and organisational effectiveness, and (5) impact on staff performance and human–AI collaboration. Together, these themes capture the key dimensions of AI implementation and its organisational outcomes, aligned with the research objectives and questions.

Across the 99 included studies, each study was mapped to a dominant theme, although some contributed to more than one theme. The most frequent theme was decision-making quality and organisational effectiveness (n = 35), followed by staff performance and human–AI collaboration (n = 26), AI applications in administrative processes (n = 14), AI adoption and digital transformation (n = 13), and administrative efficiency and productivity (n = 11).

Overall, the findings show that AI is reshaping administrative functions through five interconnected areas: digital transformation, process automation, efficiency improvement, decision support, and workforce enhancement. The results also suggest that recent research increasingly focuses on AI as a strategic organisational capability, particularly in relation to decision-making and human–AI collaboration.

AI Adoption and Digital Transformation in Administrative Functions

In this review, AI adoption and digital transformation refer to how artificial intelligence technologies are integrated into organizational administrative functions to support innovation, modernize processes, and drive broader organizational change. This theme was identified as the main focus in 13 studies, reflecting the increasing role of AI as a key driver of digital transformation across organizations.

Several studies show that AI adoption plays an important role in organizational transformation by supporting the shift from traditional administrative systems toward more intelligent, data-driven, and automated environments. For example, Heliani et al. (2026) found that combining AI technologies with cloud accounting and big data analytics improves organizational competitiveness and strengthens digital transformation efforts. Similarly, Mohamad et al. (2026) reported that AI helps organizations redesign business processes and become more adaptable in rapidly changing environments. Alsaadi et al. (2026) also noted that AI supports organizational modernization by enhancing administrative capabilities and improving digital integration across different functional areas.

Overall, the literature suggests that successful digital transformation depends not only on technology, but also on organizational readiness, technological capability, and leadership support. Quadras et al. (2026) and Quinello and Costa (2026) emphasized that AI implementation is more effective when it is guided by a clear digital strategy and strong management commitment. In the same way, Raimi (2026) and Al-Ansi et al. (2026) highlighted the importance of organizational culture and employee readiness in ensuring successful AI adoption. This indicates that AI-driven transformation should be understood as an organizational change process, where technology, people, and strategy need to work together.

Several studies also highlight how AI contributes to organizational resilience and innovation. Gontarek and Cunha (2026) found that AI helps organizations respond better to uncertainty by improving information processing and decision-making support. Likewise, Ibrahim et al. (2026) showed that organizations using AI are better able to increase operational flexibility and sustain continuous innovation. These findings suggest that AI strengthens digital transformation by improving organizational agility and enabling more responsive administrative systems.

However, despite these benefits, several challenges to AI adoption were also identified. Sezgin and Boch (2026) reported that implementation complexity, technological uncertainty, and resistance to change can slow down or hinder AI adoption. In addition, some organizations struggle with limited digital skills, weak technological infrastructure, and concerns about employee adaptation. These issues may reduce the effectiveness of transformation efforts and delay the benefits of AI implementation.

Overall, the evidence suggests that AI acts as an important catalyst for digital transformation in administrative settings. Successful adoption depends on a combination of technological readiness, organizational support, and effective change management. Future research could further explore the long-term sustainability of AI-driven transformation and identify best practices that help organizations adapt more successfully to digital change.

Applications of AI in Administrative Processes

In this review, applications of AI in administrative processes refer to the use of artificial intelligence technologies to automate, support, and improve routine administrative tasks such as information management, documentation, communication, reporting, monitoring, scheduling, and service delivery. This theme was identified as the main focus in 14 studies, showing the growing use of AI to enhance the efficiency and effectiveness of administrative work.

The reviewed studies show that AI is increasingly used to handle repetitive and time-consuming tasks. Wang et al. (2026) found that AI supports sustainability management by automating data collection, analysis, and reporting, which reduces administrative workload and improves accuracy. Similarly, Saavedra et al. (2026) reported that AI improves administrative performance through process automation and better information

management. These findings indicate that AI helps modernize administrative functions by reducing manual work and improving consistency in processes.

Several studies also highlight how AI improves communication, monitoring, and information handling within organizations. Han et al. (2026) found that AI-based governance systems strengthen monitoring and improve administrative oversight. In the same way, Cabanos et al. (2026) reported that AI-driven information systems enhance communication and knowledge management by enabling faster access to and processing of information. Overall, these studies suggest that AI allows organizations to manage large volumes of administrative data more efficiently than traditional methods.

The literature also shows an increasing use of AI-based service tools such as chatbots, virtual assistants, and intelligent support systems. Jose et al. (2026) found that these tools improve coordination and service delivery by providing faster responses and reducing delays in routine administrative interactions. Likewise, Silva (2026) reported that AI-supported systems strengthen administrative services through real-time assistance and automated support functions. These findings suggest that AI contributes to better service quality and improved user satisfaction by making organizations more responsive.

Despite these benefits, several challenges were also identified. Stein (2026) noted that over-reliance on AI-generated outputs may reduce human oversight and increase the risk of system-related failures. Similarly, Goyal et al. (2026) highlighted issues such as data quality concerns, algorithmic bias, privacy risks, and lack of transparency. These findings suggest that although AI improves efficiency, organizations need strong governance and control mechanisms to ensure responsible use.

Overall, the evidence shows that AI plays an increasingly important role in supporting administrative work through automation, better information management, and improved service delivery. It helps modernize administrative processes by making them more efficient, consistent, and responsive. Future research could explore how AI is applied in specific sectors and how organizations can balance efficiency gains with ethical, privacy, and governance considerations.

Impact on Administrative Efficiency and Productivity

Administrative efficiency and productivity refer to how well an organization carries out its administrative tasks using fewer resources, shorter processing times, and improved service quality, while still achieving better overall outputs. This theme was identified as the main focus in 11 studies, highlighting the growing importance of AI in improving efficiency within administrative settings.

The reviewed studies consistently show that AI plays a major role in improving efficiency through automation, optimization, and smarter process management. Labib et al. (2026) found that machine learning–based optimization tools improve efficiency by supporting better scheduling, planning, and resource allocation. Similarly, Jeyasheeli et al. (2026) reported that AI-supported management systems increase productivity by reducing operational disruptions and improving coordination across processes. Overall, these findings suggest that AI helps organizations make better use of resources while reducing inefficiencies.

Several studies also emphasize how AI reduces workload and speeds up administrative processes. Sun et al. (2026) found that automation significantly shortens the time needed to complete routine administrative tasks. Likewise, Yue et al. (2026) reported that intelligent workflow systems improve productivity by automating task handling and streamlining processes. These results indicate that AI allows organizations to process information faster and more consistently compared to traditional methods.

In addition, the studies show that AI improves performance through better monitoring and evaluation. Wang et al. (2026) observed that AI improves planning and resource use, which leads to higher productivity levels. Other studies also highlight that AI can identify inefficiencies and suggest improvements, supporting continuous performance enhancement. This suggests that AI not only improves day-to-day operations but also contributes to ongoing organizational improvement.

However, some studies report challenges, particularly during the early stages of implementation. Sezgin and Boch (2026) noted that productivity may temporarily decline as employees adjust to new systems and as organizations face integration issues. Similarly, Ibrahim et al. (2026) found that limited training and weak technological infrastructure can reduce potential productivity gains. These findings suggest that efficiency improvements depend on how well AI is implemented and how prepared the organization is.

Overall, the evidence indicates that AI improves administrative efficiency and productivity mainly through automation, process optimization, and better information use. However, these benefits are not guaranteed and depend on organizational readiness, employee skills, and technological capacity. Future research could further examine how these productivity gains develop over time and how they affect long-term organizational performance and competitiveness.

Impact on Decision-Making Quality and Organizational Effectiveness

In this review, decision-making quality refers to the accuracy, consistency, timeliness, and effectiveness of organizational decisions, while organizational effectiveness refers to an organization's ability to achieve strategic objectives through efficient resource utilization, performance management, and governance practices. This theme emerged as the most dominant theme, representing 35 of the 99 reviewed studies. The prominence of this theme suggests that contemporary AI research increasingly focuses on the strategic value of AI beyond operational automation, emphasizing its contribution to organizational performance and decision-making effectiveness.

The reviewed studies consistently indicate that AI enhances organizational decision-making through predictive analytics, machine learning, intelligent forecasting, and advanced data-processing capabilities. Morshed and Khrais (2026) found that AI-driven predictive analytics significantly improved institutional performance, forecasting accuracy, risk management, and customer satisfaction within financial institutions. Similarly, Akusta (2026) reported that AI-based prediction models improve lending decisions by identifying complex patterns and relationships that may not be detectable through traditional analytical approaches. These findings suggest that AI contributes to decision quality by transforming large volumes of organizational data into actionable insights that support evidence-based decision-making.

Several studies further demonstrated that AI strengthens strategic planning and organizational responsiveness. Yang et al. (2026) found that AI utilization positively influences financial operational performance by enhancing organizational capabilities and facilitating data-driven managerial decisions. Likewise, Heliani et al. (2026) reported that AI technologies improve financial reporting quality and support strategic decision-making through enhanced information processing capabilities. These findings indicate that AI enables decision-makers to evaluate alternatives more effectively, reduce uncertainty, and improve organizational performance.

The reviewed studies also highlighted the role of AI in strengthening governance, compliance, and organizational control. Han et al. (2026) found that AI-supported governance systems improve monitoring effectiveness and institutional performance by facilitating continuous analysis and reporting. Similarly, Alajmi (2026) reported that AI contributes to governance effectiveness through enhanced compliance monitoring and risk management. Ahn and Kim (2026) further observed that AI technologies support evidence-based governance by providing accurate and timely information to organizational leaders. These findings suggest that AI contributes to organizational effectiveness by improving accountability, transparency, and strategic control.

Several studies emphasized the importance of predictive intelligence as a mechanism through which AI improves decision-making quality. AI-powered systems are capable of analyzing historical and real-time data simultaneously, enabling organizations to anticipate future trends, identify potential risks, and evaluate strategic opportunities. As a result, decision-makers are better equipped to formulate proactive rather than reactive responses to organizational challenges. This capability is particularly important in dynamic and uncertain environments where rapid decision-making is essential.

Despite the predominantly positive findings, several studies reported concerns regarding transparency, explainability, and accountability. Silva (2026) argued that AI-generated recommendations may create

governance challenges when decision-making processes lack transparency and explainability. Similarly, Stein (2026) emphasized that excessive reliance on AI systems may reduce managerial oversight and increase the risk of algorithmic bias. These findings suggest that while AI can significantly improve decision quality, organizations must establish appropriate governance mechanisms to ensure accountability and ethical implementation.

Contradictory findings were also identified in several studies. Although most studies reported positive organizational outcomes associated with AI-assisted decision-making, some researchers argued that decision quality depends heavily on data quality, organizational readiness, and technological maturity. Poor-quality data, inadequate technological infrastructure, and limited employee competencies may reduce the effectiveness of AI systems and lead to suboptimal decisions. Consequently, AI should be viewed as a decision-support tool that complements rather than replaces human judgment.

Overall, the reviewed studies demonstrate that AI contributes significantly to decision-making quality and organizational effectiveness through predictive analytics, intelligent forecasting, governance enhancement, and evidence-based management. The findings suggest that AI has evolved from an operational technology into a strategic organizational capability that supports long-term performance and competitiveness. Future research should investigate explainable AI, ethical governance frameworks, and the long-term implications of AI-assisted decision-making for organizational effectiveness.

Impact on Staff Performance and Human–AI Collaboration

In this review, staff performance refers to how effectively employees carry out their work, including productivity, work quality, and achievement of organizational goals. Human–AI collaboration refers to the interaction between employees and AI systems in completing tasks and supporting decision-making within organizations. This theme emerged as the second most frequently discussed area, covering 26 of the 99 studies reviewed. Its prominence reflects growing interest in how AI is reshaping work processes, employee roles, and collaboration in the workplace.

The reviewed studies consistently show that AI improves employee performance by reducing administrative workload, automating repetitive tasks, and providing intelligent support for daily work activities. Murphy et al. (2026) found that AI-supported systems increase productivity by handling routine tasks and making organizational knowledge more accessible. Similarly, Mohammed and Guillet (2026) reported that AI enhances workforce effectiveness by improving access to information and supporting decision-making in operations. Overall, these findings suggest that AI helps employees work more efficiently by allowing them to focus less on routine tasks and more on value-added activities.

Several studies also highlight that AI is increasingly seen as a working partner rather than just a tool for automation. Pluskota et al. (2026) observed that by taking over routine administrative tasks, AI allows employees to concentrate on more complex work that requires creativity, problem-solving, and strategic thinking. Likewise, Gramifar et al. (2026) found that AI supports employees through task assistance and real-time recommendations. These findings indicate that AI works alongside employees in a complementary way, strengthening human capabilities rather than replacing them.

The literature also suggests that AI contributes to employee learning and skill development. As AI becomes more integrated into workplace systems, employees are often required to develop new digital skills and adapt to changing technologies. Several studies noted that this process encourages continuous learning and improves workforce adaptability over time. This indicates that AI adoption not only changes how work is done but also influences how employees grow professionally.

Another important finding is the role of AI in supporting decision-making. AI systems provide real-time insights, predictions, and analytical outputs that help employees make more informed decisions. This is especially useful in administrative environments where large amounts of data must be processed quickly and accurately. By combining human judgment with AI-generated insights, organizations can improve both individual performance and overall outcomes.

However, several concerns were also identified. Mhlanga (2026) noted that AI adoption may create uncertainty about job security and future work roles. Similarly, Ratshalingwa and Civilcharran (2026) reported that some employees worry about being replaced by automated systems. These concerns suggest that employee perceptions of AI can influence how well it is accepted and implemented within organizations.

Some studies also reported mixed effects on employee well-being. While AI can improve productivity and performance, it may also lead to increased workload, stress, or concerns about skill relevance, especially if organizations do not provide sufficient training and support. This shows that the impact of human–AI collaboration depends not only on technology but also on how well organizations manage the transition.

Overall, the findings suggest that AI can improve staff performance when it is used to support rather than replace human work. Effective human–AI collaboration requires continuous training, skill development, and strong change management practices. Future research could further explore how AI affects employee well-being, job satisfaction, and long-term workplace dynamics as organizations continue to adopt intelligent systems.

CONCLUSION

This systematic literature review synthesizes findings from 99 peer-reviewed studies to examine the impact of Artificial Intelligence (AI) on administrative functions and organizational performance. The results show that AI is transforming administration through five key areas: AI adoption and digital transformation, applications in administrative processes, administrative efficiency and productivity, decision-making quality and organizational effectiveness, and staff performance with human–AI collaboration.

Among these, decision-making quality and organizational effectiveness is the most prominent area, indicating that AI is widely used to support better decisions, forecasting, governance, and strategic performance. Across the studies, AI is not limited to operational support but is increasingly used to improve strategic and data-driven decision-making.

The review also shows that AI enhances administrative processes through automation and optimization, leading to improved efficiency, reduced workload, and better service delivery. It also supports digital transformation by helping organizations modernize systems and adapt to change. In addition, human–AI collaboration is an important outcome, where AI supports employees and improves performance rather than replacing human roles.

Despite these benefits, several challenges remain. These include organizational readiness, workforce adaptation, ethical issues, lack of transparency, and data quality concerns. This shows that successful AI implementation depends on both technological and organizational factors.

This study contributes in three ways. First, it provides a clear framework that integrates fragmented findings on AI in administration. Second, it offers a transparent synthesis of 99 studies using a systematic review approach. Third, it provides practical guidance for managers and policymakers on the conditions needed for effective AI adoption.

The review also addresses a gap in previous research, which often focused on specific tools or limited outcomes. By integrating evidence across sectors and contexts, this study offers a more complete understanding of AI's role in administrative performance, decision-making, and workforce outcomes.

Future research should examine the role of organizational culture in AI adoption and digital transformation, particularly through longitudinal studies. It should also explore explainable AI and its impact on trust and decision quality. In addition, more studies are needed on the long-term effects of human–AI collaboration on employees, as well as comparisons of AI governance frameworks and the effectiveness of training and reskilling programs.

Overall, AI presents strong potential to improve organizational performance, but its success depends on balancing technological advancement with ethical responsibility and human considerations. This balance is essential for achieving sustainable and responsible organizational development.

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