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The compare of the Impact of Artificial Intelligence Techniques on Task Accuracy and Speed Compared to Traditional Approaches

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Abstract

Artificial Intelligence (AI) plays a critical role in enhancing task performance across sectors such as healthcare, education, manufacturing, and agriculture. By utilizing advanced algorithms, machine learning, and data analytics, AI enhances the accuracy and speed of task execution. This study compares AI-powered techniques with traditional task management methods, including rule-based systems, manual processes, and heuristic algorithms. While AI excels in handling complex, data-intensive tasks with higher accuracy and efficiency, traditional methods remain valuable due to their simplicity, transparency, and lower resource requirements.

This work explores the strengths, limitations, and practical applications of both approaches across various industries by reviewing prior research and comparing their outcomes. It identifies areas where hybrid models may prove most effective. Furthermore, it highlights AI's contribution to improving efficiency and accuracy while demonstrating that integrating AI with traditional methods offers a strategic solution that combines speed, precision, and transparency.

The study concludes with recommendations for guiding AI adoption and enhancing task performance strategies. It also suggests directions for future research to further develop both AI-supported techniques and traditional methods.

Keywords: Artificial Intelligence, Traditional task management, Machine learning, Task scheduling algorithms**.**

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مقارنة تأثير تقنيات الذكاء الاصطناعي على دقة وسرعة المهام مقارنة بالأساليب التقليدية

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الملخص

يلعب الذكاء الاصطناعي (AI) دورًا حاسمًا في تحسين أداء المهام عبر قطاعات مثل الرعاية الصحية، والتعليم، والتصنيع، والزراعة. من خلال استخدام الخوارزميات المتقدمة، والتعلم الآلي، وتحليلات البيانات، يعزز الذكاء الاصطناعي من دقة وسرعة تنفيذ المهام. تقارن هذه الدراسة بين التقنيات المدعومة بالذكاء الاصطناعي وأساليب إدارة المهام التقليدية، بما في ذلك الأنظمة القائمة على القواعد، والعمليات اليدوية، والخوارزميات الاستدلالية. بينما يتفوق الذكاء الاصطناعي في التعامل مع المهام المعقدة وكثيفة البيانات بدقة وكفاءة أعلى، تظل الأساليب التقليدية ذات قيمة بسبب بساطتها وشفافيتها وانخفاض احتياجاتها من الموارد. تستكشف الدراسة نقاط القوة والقيود والاستخدامات العملية لكل من النهجين عبر الصناعات المختلفة، من خلال دراسة الابحاث السابقة ومقارنتها مع تحديد المجالات التي قد تكون فيها النماذج الهجينة الأكثر فعالية. وتوضح من خلالها مساهمة الذكاء الاصطناعي في تحسين الكفاءة والدقة ودمجه مع الوسائل التقليدية يعطي حل استراتيجي يجمع بين مزايا السرعة والدقة والشفافية وتختتم بتوصيات لتوجيه تبني الذكاء الاصطناعي وتحسين استراتيجيات أداء المهام، إلى جانب اقتراحات لأبحاث مستقبلية لتعزيز كل من التقنيات المدعومة بالذكاء الاصطناعي والأساليب التقليدية.

الكلمات المفتاحية: الذكاء الاصطناعي، إدارة المهام التقليدية، التعلم الآلي، خوارزميات جدولة المهام.

1. Introduction

The pace of innovation in the recent past, especially in the case of AI, has transformed every sphere that depends on technology. AI mechanisms analyze volumes of data and come out with patterns, using their capabilities for intelligent and quick decisions. In the development of higher task performance, their value is properly

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acknowledged in manufacturing, healthcare, education, and financial services that assure greater efficiency and lower costs.

Despite the rapid progress on deploying AI technologies, earlier work surprisingly lacked comprehensive comparative analyses setting them in perspective against traditional approaches; approaches that are relatively simple and transparent and require fewer resources are still relevant in a lot of contexts. Traditional approaches, though, are the commonest in tasks whose applications call for interpretability, which demands very minimal or no infrastructure. However, there is a lack of explicit examination on their comparative effectiveness, especially toward their trade-off between speed and accuracy.

Most of the literature so far has focused only on the performance of AI and fails to take into consideration when and how traditional methods may be superior. There is also a lack of research into hybrid models that would put together the best capabilities of AI with the reliability and simplicity of traditional approaches.

The rapid adoption of AI is creating urgent questions about its relative effectiveness as compared to traditional methods, especially in contexts where balancing task accuracy and speed is critical. While AI is especially good at handling complex, data-intensive tasks, traditional methods still have their relative advantages in particular situations. Moreover, there is limited exploration regarding how hybrid models can integrate strengths of AI while ensuring the transparency and efficiency provided by traditional methods.

Such ambiguity significantly impairs the ability of decision-makers to select the most appropriate approach for the achievement of optimal task performance across diverse fields. This paper, therefore, tries to bridge these gaps by giving a detailed analysis of how AI enhances accuracy and speed as compared to traditional methods. It will also debate challenges and limitations in integrating these approaches, hence contributing to the development of data-driven strategies that support decision-making for improved performance in various fields.

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2. Literature Review

Traditional approaches often offer reliable but slower and less flexible task performance compared to modern AI-enhanced methods. In fields like foreign language learning, traditional methods such as grammar-translation focus on the thorough study of grammar and vocabulary but lack the communicative competence required for real-world use, leading to slower acquisition of language skills [1]. Similarly, in medical diagnostics, traditional microbial identification methods are accurate but time-consuming, often taking hours or days to process and analyze pathogens. While effective, they cannot match the speed of modern molecular diagnostics like PCR or mass spectrometry, which significantly accelerate diagnosis times while maintaining high accuracy [2]. Studies in cognitive science also highlight that traditional hierarchical models in testing do not account for the speed-accuracy tradeoff, which can affect both performance and decision-making in time-constrained tasks, where examinees must balance between speed and precision [3].

Traditional task management in computers, before the integration of AI, relied heavily on methods such as rule-based systems, hierarchical task scheduling, and manual inputs for resource allocation and execution. In task management systems, conventional approaches often used task-relating branch prediction data stored in branch prediction history tables, which allowed the computer to manage tasks by predicting future actions based on previously executed tasks, such as in processor task management [4]. Another traditional method involved task allocation via organizational datasets, where databases stored task-specific data objects linked to specific entities, enabling task execution based on predefined workflows and properties [5]. Traditional task management systems also involved apparatuses that prompted users based on preset conditions, ensuring that tasks were executed based on specific predefined criteria, with minimal automation beyond user inputs [6].

Artificial intelligence (AI) techniques significantly enhance both task accuracy and speed when compared to traditional approaches across various fields. In administrative processes, AI-driven

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automation improves accuracy by reducing human errors, speeding up workflows, and optimizing resource allocation through predictive decision-making tools like natural language processing and predictive analytics [7]. Similarly, in business, AI's ability to rapidly process and analyze large datasets enhances operational efficiency, reducing task completion time while improving decision accuracy [8]. A study in medical imaging demonstrated that AI support in breast cancer detection increased diagnostic accuracy and reduced reading times for radiologists compared to manual interpretations, highlighting AI's capacity to surpass human capabilities in specific, high-stakes tasks [9]. AI also plays a vital role in lung cancer detection during the COVID-19 pandemic, where it accelerates the diagnosis process while maintaining accuracy, especially in distinguishing between different types of lung conditions [10]. Overall, AI's precision and speed provide clear advantages over traditional methods, but challenges like employment shifts and ethical considerations remain critical for its broad adoption.

The comparison between AI techniques and traditional approaches reveals mixed results depending on the application. In the ecological domain, AI techniques like YOLOv5 and EfficientDet-D7 significantly improved accuracy and speed in seagrass detection, outperforming traditional methods by up to 7% while also processing images in a fraction of the time [11]. However, AI-human collaboration in educational skill tagging demonstrated that while AI sped up task execution by 50%, it compromised accuracy by 35%, compared to traditional human-only approaches [12]. Business management similarly benefits from AI-powered automation, where repetitive tasks are handled more swiftly and with greater precision than manual methods, though concerns over the loss of human touch persist [13]. In education, AI-enabled speaking evaluations for ESL learners revealed discrepancies between human and AI assessments, suggesting AI still lags in areas requiring nuanced understanding [14]. Finally, AI-based multi-task networks in breast ultrasound diagnosis demonstrated superior time efficiency and accuracy over traditional deep learning models, underscoring AI's potential in medical applications [15].

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Artificial intelligence (AI) significantly enhances efficiency in environmental monitoring tasks by integrating advanced technologies such as remote sensing, the Internet of Things (IoT) [16], and machine learning (ML). AI-driven systems streamline data collection, processing, and analysis, allowing for more accurate and faster monitoring compared to traditional methods. For example, AI models like the Modified VGG16 improve land cover classification accuracy by up to 97%, significantly outperforming manual processes in precision and speed. Additionally, IoT-enabled environmental monitoring systems, powered by AI algorithms, enable real-time analysis of environmental changes, enhancing predictive capabilities and decision-making processes in areas like air and water quality [17]. AI also supports sustainable management of ecosystems by automating the detection of pollutants and other hazards, reducing the time and effort required for manual data collection and analysis, which traditionally is labor-intensive and error-prone [18]. Moreover, AI-driven tools are crucial in marine and biodiversity monitoring, where vast amounts of data can be analyzed efficiently, offering unprecedented insights into ecosystem health and sustainability efforts [19].

The integration of AI in educational settings offers substantial potential but also faces notable challenges that need to be addressed for successful implementation. One major concern is data privacy, as AI systems often rely on collecting and processing large amounts of sensitive information, raising ethical issues surrounding data security and consent [20]. Additionally, algorithmic bias presents a significant challenge, where AI models may reinforce pre-existing inequalities if not properly designed, leading to unfair outcomes in educational assessments and opportunities [21]. The digital divide further exacerbates these issues, as unequal access to technology can widen educational disparities, preventing some students from fully benefiting from AI-powered tools [22]. Moreover, technical infrastructure and teacher training must be improved to ensure the effective adoption of AI in classrooms, as many educators lack the skills needed to integrate these technologies effectively into their teaching practices [23]. Ethical concerns around maintaining human-centered education, where AI enhances but does not replace

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teacher-student interactions, remain critical in discussions about the future of AI in education [24].

AI plays a transformative role in real-time environmental data analysis by enabling faster, more accurate, and adaptive monitoring systems. AI-driven methods, such as machine learning algorithms and deep learning models, enhance the processing of vast environmental datasets collected from IoT devices, satellites, and sensors, providing timely insights into environmental changes. For instance, in IoT-based environmental monitoring systems, AI optimizes data quality, predictive analytics, and decision-making processes, making it easier to detect and forecast environmental changes like air quality fluctuations or pollution spikes in real-time [25]. AI integration in real-time air quality monitoring enhances predictive capabilities by combining weather data and pollution analysis, allowing policymakers to make informed decisions swiftly [26]. Moreover, AI systems like GRU-Auto encoders paired with IoT platforms offer advanced real-time monitoring for sustainable energy management and environmental monitoring, ensuring that data is processed efficiently and environmental trends are predicted with high accuracy [27].

AI improves real-time air quality monitoring by integrating advanced technologies such as IoT, machine learning, and predictive analytics to offer precise, efficient, and timely assessments of air pollution. AI-driven systems, combined with IoT sensors, gather data on pollutants like CO2 [28], VOCs, and particulate matter, and analyze it in real-time, providing critical insights for timely interventions. For instance, a real-time monitoring system using AI-based IoT sensors in Sivakasi, India, successfully tracked pollutants like NO2 and SO2, while AI algorithms such as SARIMA provided accurate pollutant forecasts, allowing for better prediction and control of air quality. Moreover, systems like Air-IoT use deep learning models (DenseNet) to classify air quality in urban areas, providing real-time alerts when pollution levels exceed safe thresholds, thus improving both spatial coverage and accuracy [29]. AI-powered tools also enhance mobility by integrating drone technology with machine learning, allowing fine-grained air quality assessments in different altitudes and

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locations, revolutionizing traditional stationary monitoring methods [30].

3. Objectives of the Research

For an effective comparison of techniques between AI and traditional methods, the focus should be on specific tasks such as medical diagnostics, logistics management, and financial forecasting. Such domains have been chosen because they require both accuracy and speed, hence making them very apt for assessing the strengths and weaknesses of each approach. It begins with a metrics definition for execution accuracy, considering things like error rates, model sensitivity, and positive predictive values of interest that would give some approximation for the effectiveness of the approaches in the production of trustworthy results. Besides accuracy, the review also looks into the execution speed, assessing how long each of the methods takes to complete a task. This analysis highlights scenarios where AI excels in rapid decision-making and those where traditional methods provide comparable or superior efficiency.

It also examines the strengths and weaknesses of both AI and traditional approaches with respect to such critical factors as resource requirements, scalability, and operational complexity. This analysis has brought into sharp focus the contexts in which each method is most advantageous and the trade-offs involved.

A data-driven comparative framework is designed in order to summarize these findings and point out how AI and traditional methods differ for the selected tasks. This framework provides actionable recommendations that can guide decision-makers on how to choose the best approach based on the criteria of accuracy, speed, and practicality in real-world applications.

4. Methodology of the study

A structured approach will be done to ensure that the review of the literature comparing AI techniques with traditional methods for task performance regarding accuracy and speed is systematic and comprehensive. The process begins with the identification of relevant studies through a thorough search of reputable academic

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databases such as PubMed, IEEE Xplore, and Scopus. The keywords used will then involve "AI task performance," "accuracy comparison," "execution speed," "traditional methods," and "hybrid models" to ensure the inclusion of studies from diverse fields and applications. It thus sets inclusion criteria that considers the studies which would directly compare AI to traditional methods within selected domains of interest like healthcare, logistics, and financial forecasting. It further excludes the ones that lack appropriate details of methods that were reviewed, or that not related to performance metrics at tasks. Then, eligible studies are analyzed in depth, and the extracted data on the nature of tasks studied, evaluation methods applied, and contexts in which comparisons were performed is discussed. It will summarize and categorize findings on critical factors such as types of tasks addressed, performance metrics defined, and observed outcomes regarding both AI and traditional approaches. This will provide a deeper understanding of the strengths and weaknesses of each approach through systematic organization of the literature to arrive at well-informed insights and recommendations.

4.1. Literature Search Strategy

A comprehensive search will be conducted in academic databases such as Google Scholar, IEEE Xplore, SpringerLink, PubMed, ResearchGate, ScienceDirect and PLOS ONE. These databases were chosen because they provide access to peer-reviewed articles, conference papers, and technical reports relevant to artificial intelligence, computing methods, and performance comparisons.

4.2. Exclusion Criteria

Studies without empirical data or comparative analyses are excluded as they lack the reliable evidence needed to draw meaningful conclusions about AI performance compared to other methods. Empirical data provide measurable outcomes, while comparative analyses directly evaluate strengths and weaknesses. Without these elements, such studies rely on theoretical assumptions and fail to demonstrate how AI performs relative to traditional methods, making them unsuitable for a systematic review focused on performance metrics.

5. Classification and Synthesis of Results

a. Thematic Grouping

- **Healthcare:** Studies on medical diagnostics, such as breast cancer detection [31] and lung cancer detection during the

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COVID-19 pandemic [32], demonstrate how AI improves diagnostic accuracy and reduces reading times compared to traditional methods like manual interpretations.

- **Logistics and Business:** AI-driven automation in logistics management [33] improves speed and accuracy by optimizing resource allocation and reducing human errors.
- **Financial forecasting** benefits from AI's ability to analyze large datasets quickly, improving decision accuracy [34].
- **Education:** AI is used for skill tagging in education, improving speed but compromising accuracy in some cases [35]. Also AI-enabled speaking evaluations in language learning for ESL students showed discrepancies compared to human assessments, indicating AI's limits in nuanced tasks [36].
- **Environmental Monitoring:** AI in real-time environmental monitoring [37] improves the speed and accuracy of land cover classification compared to traditional manual methods. AI's integration with IoT devices in environmental monitoring provides more accurate, real-time data on pollutants, enabling faster decision-making [38].

b. Comparative Analysis

Table 1: A compare between AI and traditional aspects

Aspect	***AI***	***Traditional Methods***
Accuracy	Consistently outperforms traditional methods in precision-demanding tasks, e.g., medical diagnostics [39] and environmental monitoring.	Relatively lower accuracy; for instance, grammar-translation methods in language learning slow down skill acquisition.
Speed	Significantly accelerates tasks in fields like medical diagnostics [40], environmental monitoring, and financial forecasting. However, speed gains may sometimes come at the	Slower task execution in data-intensive tasks; however, maintains steadier accuracy in educational and less complex scenarios.

	cost of accuracy in specific contexts.	
Efficiency	Excels in processing large datasets quickly and accurately, especially in business and logistics [41].	Struggles with large datasets due to limitations in computational and methodological scalability.
Study Robustness	Demonstrates robust methodology with clear results in studies like breast cancer detection and seagrass detection. Financial forecasting is highly reliable due to predictive modeling techniques.	Methodologies are often simpler and lack the scalability of AI-powered analyses, making them less robust in large-scale studies.
Appropriateness of Algorithms	Uses advanced techniques like deep learning (e.g., CNNs for medical imaging) and machine learning for complex pattern recognition and large-scale analysis.	Relies on straightforward algorithms or rule-based systems, effective for simpler, well-defined tasks but unsuitable for complex data scenarios.

c. Overview of traditional approaches

Table 2: Overview of traditional approaches

Traditional Approach	***Description***	***Limitations***
First Come, First Serve (FCFS)	Tasks are executed in arrival order, but it's inefficient in high-demand environments [42]	Inefficient in high-demand environments.
Shortest Job First (SJF)	Prioritizes shorter tasks for better	May delay longer tasks.

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	throughput but may lead to longer tasks being delayed [43]	
Round Robin (RR)	Time-sharing algorithm that ensures fairness but can cause inefficiencies if the time slice is poorly calibrated.[44].	Can cause inefficiencies if time slice is poorly calibrated.
Task Scheduling in Cloud Computing (Min-Min, Max-Min, OLB)	Methods like Min-Min and Max-Min algorithms, and Opportunistic Load Balancing (OLB), aim to allocate tasks based on execution time or resources, but they struggle with handling dynamic workloads effectively [45]	Struggles with handling dynamic workloads effectively.

6. Overview of AI-Based Approaches

Table 3: Overview of AI-Based Approaches

AI Techniques Overview	AI techniques improve task performance by enhancing accuracy, speed, and efficiency, using ML, DL, and neural networks.
Machine Learning (ML)	ML allows systems to learn from data, with supervised learning for accuracy in tasks like medical diagnostics and unsupervised learning for detecting hidden patterns in large datasets.

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Unsupervised Learning	Unsupervised learning identifies patterns without labeled data. It's used for tasks like clustering and market segmentation. Traditional methods struggle in large datasets [46].
Deep Learning (DL)	DL uses neural networks to model complex patterns, with CNNs excelling in image processing and RNNs for time-series forecasting [47].
Reinforcement Learning (RL)	RL optimizes real-time decision-making in areas like autonomous driving and robotics through trial and error [48].
AI for Predictive Maintenance	AI predicts equipment failures using sensor data, improving efficiency over traditional maintenance schedules based on fixed intervals [49].
Hybrid AI Systems	Combines traditional methods with AI, such as fuzzy logic with neural networks, to improve decision-making and accuracy [50].
AI Techniques Overview	AI techniques improve task performance by enhancing accuracy, speed, and efficiency, using ML, DL, and neural networks [51].

7. Key Findings and discussion

- **Decision-Making Speed:** The AI systems can make decisions within a fraction of a second, which is not possible to make manually, especially in complicated tasks. Though the traditional systems might compete in speed for repetitive or low-scale tasks, they lag behind in high-complexity tasks. However, such a fast pace of decision-making also gives rise to

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ethical concerns over data privacy and security, since AI systems rely on vast volumes of sensitive data. It is important that AI be used responsibly in high-speed decision-making to meet these challenges.

- **Complexity and Scalability:** AI thrives in large-scale, dynamic environments such as cloud computing and autonomous systems, adapting to changing workloads. Traditional methods struggle with scalability, making them less suitable for such environments. Whichever the case, the widespread use of AI might exacerbate the digital divide if access to advanced technologies is not distributed equitably, leading to increased societal inequalities.
- **Limitations and Trade-offs:** AI requires substantial computational power, quality data, and expertise for ideal performance. Traditional methods, though at the expense of adaptability, provide transparency, ease of application, and do not require any state-of-the-art infrastructure. In addition, heavy reliance on AI may raise serious job losses in traditional method-based sectors, imposing huge social and economic burdens on societies. Innovation should keep pace with workforce adaptation as part of the balancing in dealing with these issues.
- **Hybrid Models:** Combining AI with traditional methods provides a promising strategy, leveraging both strengths. For example, AI-powered scheduling combined with human oversight ensures both efficiency and transparency in decision-making. However, the integration of AI into such hybrid models needs to consider ethical implications, particularly in ensuring that the technology does not reinforce bias or perpetuate inequalities.

- **Healthcare:** AI surpasses the current methodologies in medical diagnostics through large-scale datasets for quicker and more correct predictions. However, most AI models are "black box" in nature, thereby raising clinician trust issues and regulatory and data privacy challenges. These concerns make us think of the need for transparent AI models and specific guidelines that can overcome all ethical issues in healthcare.

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- **Logistics and Supply Chain:** AI improves operational efficiency in logistics by automating scheduling and optimizing inventory. Traditional techniques continue to work well for stable, low-complexity tasks for which interpretability and reduced resource requirements are more critical. The wider diffusion of AI in these sectors needs to be governed to ensure it doesn't lead to more job losses or add to growing inequality.AI enhances financial forecasting by processing large data sets and performing calculations automatically. Traditional models still play a vital role in validating AI outputs for regulatory compliance and in order to maintain investor confidence. The economic impact of AI in finance is huge, and if not well policed by appropriate policies, it has the potential to widen the gap between those who can access AI tools and those who cannot, further increasing inequality
- .**Financial Services:** AI improves financial forecasting by processing large datasets and automating calculations. Traditional models still play an important role in validating AI outputs for **regulatory compliance** and maintaining investor confidence.
- **Risk of Bias and Quality Assessment:** AI systems could be biased and flawed, particularly when their training involves small or low-quality data. For better assurance of the performance quality in AI, it is crucial to ensure diversity in the data and transparency in methodologies. In addition, there are ethical concerns on how AI models can amplify existing societal inequalities, hence the need for stringent quality assessment in training data.
- **Gaps and Future Research:** There is a need for further research to establish how well the hybrid AI-traditional system is working in real-time for applications such as self-driving cars and education. Also, there is a need for improvement in AI interpretability to ensure wider adoption in critical areas such as healthcare. Meeting these challenges, together with consideration of the social and economic consequences of the integration of AI, will be crucial to inform further development and ensure that benefits from AI are equitably shared.

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8. Conclusion

This study has proved that AI techniques are far better than traditional methods in terms of accuracy and speed, especially when dealing with complex tasks. However, traditional methods are still valued because of their simplicity and lower resource requirements. Hybrid models that combine both AI and traditional approaches are recommended for further development, while ethical issues such as privacy and bias should be addressed to ensure fairness and sustainability. Futures studies must be geared toward more efficient development of hybrid models, addressing the challenge of AI in privacy and bias, improvements in AI systems, assessment of long-term implications of AI deployment, and studies on economic and social impacts from adopting AI technologies.

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