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Balancing AI Efficiency and Ethics for Long-Term Business Sustainability

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***Abstract*: Artificial Intelligence (AI) integration reshapes organisational decision-making, yet its sustainability implications remain underexplored. This study examines the impact of AI on productivity, economic viability, and ethical considerations in mid-sized companies across the healthcare, finance, and manufacturing sectors. Using a mixed-methods approach, data were collected from 50 AI-integrated firms through surveys and stakeholder interviews. Quantitative analysis (using SPSS and R) revealed that AI reduced task completion time by 40% and error rates by 80%, resulting in a net annual benefit of $1.27 million and a payback period of one year. However, ethical challenges emerged, including algorithmic bias (detected in 12% of AI-driven decisions) and concerns about transparency, necessitating robust governance frameworks. A novel mathematical model incorporating a sigmoid function was developed to balance efficiency gains with ethical risks. Findings suggest that AI enhances operational efficiency and financial returns; however, its long-term sustainability depends on effective bias mitigation, regulatory compliance, and employee adaptation strategies. This research provides a comprehensive framework for sustainable AI adoption, guiding businesses in maximising efficiency while ensuring equitable and transparent decision-making. The study contributes to sustainability discourse by bridging AI-driven innovation with responsible governance, fostering resilient and adaptive business models.**

***Keywords*: Artificial Intelligence (AI), Sustainable Decision-Making, Operational Efficiency, Algorithmic Bias, Economic Viability, Ethical AI Governance.**

1. Introduction

Organisational decision-making has undergone significant transformations over the decades. Initially, decisions were predominantly based on intuition and the personal experiences of leaders, a practice known as intuition-based decision-making [1], [2]. This approach relied heavily on human judgment and qualitative assessments, which, although valuable, were often limited by cognitive biases and a lack of comprehensive data analysis [3], [4]. Leaders often make choices based on gut feelings, past experiences, and anecdotal evidence, which can sometimes lead to inconsistent outcomes [5]-[7]. The advent of information technology and the increasing availability of data in the late 20th century marked a shift towards data-driven decision-making. Organisations began to collect and analyse quantitative data to inform their strategies, using statistical tools and software to identify trends and patterns [8], [9]. This approach reduced reliance on subjective judgment, allowing for more consistent and measurable decision-making outcomes [10], [11]. Data warehouses and business intelligence tools became integral, enabling organisations to harness historical data for forecasting and planning. In recent years, the emergence of Artificial Intelligence (AI) and machine learning has ushered in a new era: AI-driven decision-making [12]-[14]. Unlike traditional data analysis methods, AI algorithms can process vast amounts of structured and unstructured data in real-time, learning from each interaction to continually improve accuracy [15]-[17]. This capability allows organisations to uncover complex patterns and insights that were previously inaccessible, facilitating predictive analytics and more proactive decision-making. AI-driven approaches minimise human biases and errors, offering a level of precision and speed unattainable by human analysts alone [18]-[20].

AI and machine learning have been integrated into various business operations, revolutionising organisations' functions [20]-[22]. In supply chain management, AI algorithms optimise logistics by predicting demand fluctuations, adjusting inventory levels, and selecting optimal shipping routes, reducing costs and improving efficiency [22]-[24]. Machine learning models analyse customer behaviour in marketing to personalise recommendations and advertising content, enhancing customer engagement and conversion rates [25], [26]. Financial institutions leverage AI for fraud detection and risk management. Machine learning models scrutinise transaction patterns to identify anomalies indicative of fraudulent activities, enabling quicker responses to potential threats. AI assists talent acquisition in human resources, automating resume screening

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and predicting candidate suitability based on historical hiring data [27]-[29]. Additionally, AI-powered chatbots and virtual assistants improve customer service by providing instant support and handling routine inquiries, freeing human agents to focus on more complex issues [30]-[32]. These applications demonstrate AI's capacity to automate routine tasks, enhance data analysis, and support complex decision-making processes across various organisational departments, increasing operational efficiency and competitiveness [33]-[35].

This research explores the transformative role of Artificial Intelligence (AI) in enhancing organisational decision-making across multiple dimensions—operational, economic, and ethical. Specifically, the study aims to quantify AI's impact on productivity metrics, such as task completion time, error rates, and revenue generation, while evaluating its financial viability and payback period. Additionally, the research seeks to address the ethical implications of AI integration, including algorithmic bias and transparency, by proposing a model that balances operational gains with ethical considerations. By examining these factors, the study provides a comprehensive framework to guide organisations in maximising AI benefits, ensuring ethical compliance, and achieving sustainable performance improvements, making AI a viable asset in strategic decision-making processes. Fig. 1 shows a flow diagram visually outlining the methodology for assessing AI integration's impact. It begins with defining objectives, followed by data collection (quantitative and qualitative), analysis, triangulation, ethical and cost-benefit assessment, mathematical modelling, and performance evaluation. The process ends with identifying outcomes and providing a comprehensive approach to evaluating operational, economic, and ethical dimensions.

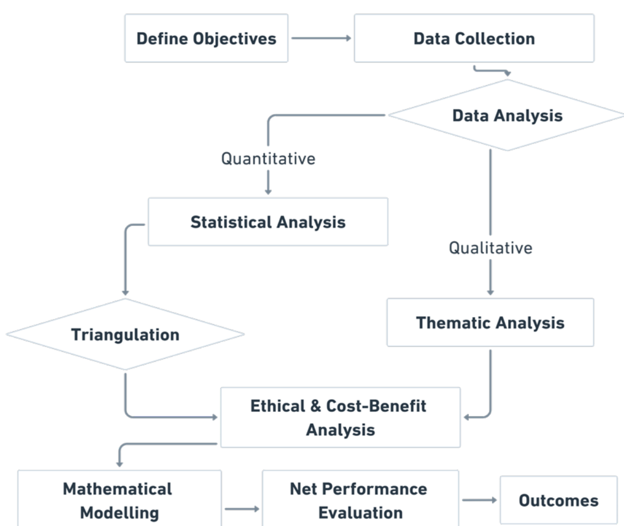


Fig. 1. Methodology framework for evaluating ai integration in organisational decision-making

2. Methodology

The methodology employed in this research combines quantitative and qualitative approaches to thoroughly assess AI's effects on organisational decision-making. The primary focus was understanding how AI enhances productivity, economic gains, and ethical accountability. The study used a mixed-method approach to gain statistical and experiential insights. Data was collected from 50 mid-sized companies across various industries, including finance, healthcare, and manufacturing. These companies were chosen for their early adoption of AI technologies, providing a relevant sample to assess AI's impact. Quantitative data was gathered through surveys, with questions designed to capture metrics such as task completion times, sales conversion rates, error reduction, and productivity indices [34]-[36]. Additionally, in-depth interviews with key stakeholders in AI-integrated departments, including IT, operations, and human resources, collected qualitative data. Interviews focused on ethical challenges, employee adaptation to AI, and operational changes post-AI implementation.

A. *Qualitative Quantitative Analysis*

Statistical tools like SPSS and R were used to process the survey data for quantitative analysis. Descriptive statistics summarised core metrics, while inferential techniques, including regression analysis, helped identify relationships between AI integration levels and improvements in performance indicators. Specifically, regression models assessed how AI affected error rates, task completion times, and revenue generation, while correlation analysis explored the link between AI-driven productivity and economic gains [36]-[38]. Thematic analysis was applied to interview transcripts using NVivo software to identify recurring themes related to operational impacts, ethical considerations, and employee experiences. The themes were coded and categorised into key areas such as ethical accountability, efficiency gains, and employee perceptions, providing a nuanced view of how AI integration affects organisational culture and workflows. Triangulation was employed to cross-validate findings from surveys, interviews, and case studies, increasing the study's validity.

B. *Ethical and Cost-Benefit Analysis*

A cost-benefit analysis was conducted to quantify AI's economic impact. This analysis assessed initial AI implementation costs (software, hardware, training) and ongoing operational expenses (maintenance and upgrades). These costs were then compared to annual benefits, including increased revenue, cost savings from improved productivity, and reduced error rates. The yearly net benefit of $1.27 million was calculated, and a payback period of one year was established, providing a clear picture of AI's financial feasibility. Ethical dimensions were evaluated by examining potential algorithmic biases and transparency issues. The research introduced a novel mathematical model incorporating a sigmoid function to balance operational efficiency gains against ethical risks. This model helped gauge the realistic net performance improvements, accounting for both AI integration's positive impacts and moral costs. This comprehensive methodology ensures a balanced understanding of AI's impact, combining measurable quantitative results with qualitative insights that illuminate organisational changes and ethical concerns.

Table 1
Cost-Benefit analysis of AI integration

Cost/Benefit Component	Description	Estimated value ($)
AI Software and Licenses	Purchase of AI applications, licenses, and subscriptions	$500,000
Hardware Infrastructure	Servers, GPUs, and other hardware required for AI processing	$300,000
Implementation Services	Consultancy fees, customisation, and integration services	$200,000
Training and Development	Employee training programs and skill development	$150,000
Data Acquisition and Preparation	Costs associated with collecting and preparing data	$100,000
Total Initial Investment		**$1,250,000**
	Annual Operational Costs	
Maintenance and Support	Ongoing technical support and system maintenance	$100,000
Updates and Upgrades	Software updates and hardware replacements	$80,000
Additional Training	Continuous learning programs for staff	$50,000
Total Annual Costs		**$230,000**
	Projected Annual Benefits	
Increased Revenue	Additional income from improved products/services	$800,000
Cost Savings	Savings from operational efficiencies and reduced labour costs	$400,000
Productivity Gains	Value derived from increased employee productivity	$300,000
Total Annual Benefits		$1,500,000
Net Annual Benefit	Total Annual Benefits - Total Annual Costs	$1,270,000
Payback Period	Initial Investment / Net Annual Benefit	Approximately one year

3. Mathematical Model

To quantitatively assess the impact of AI integration on organisational decision-making, we propose a novel mathematical model that encapsulates the ethical, operational, and economic implications into a single performance metric.

$$P_{AI} = (E_{op} \times S(\Delta O - \Delta E)) - (C_{AI} + C_{eth}) \quad (1)$$

P_{AI} is Net performance improvement due to AI integration and E_{op} economic gain from operational improvements (e.g., increased revenue, cost savings). S(ΔOΔE) is a Sigmoid function modelling the balance between operational efficiency gains and ethical risk factors. ΔO is a change in operational efficiency due to AI (dimensionless, e.g., percentage increase), and ΔE is an ethical risk factor increase due to AI (dimensionless). C_{AI} *is the* Cost of AI implementation (technology, infrastructure, training), and C_{eth} is the cost associated with ethical compliance measures, bias mitigation, and data privacy safeguards.

The Sigmoid function S(ΔOΔE) is defined as:

$$S(\Delta O \Delta E) = \frac{1}{1 + e^{-\alpha(\Delta O - \beta \Delta E)}} \quad (2)$$

α is the parameter controlling the sensitivity to changes in operational efficiency, and β represents the weight of ethical risks relative to operational gains with e Euler's number (approximately 2.71828). This equation quantifies the net performance improvement from AI integration, balancing economic gains and operational efficiency against implementation costs and ethical risks to provide a comprehensive framework for evaluating organisational impact.

A. Advanced Mathematical Model

This work defines the Net Organizational Impact (NOI) of AI integration as a function of operational efficiency, economic returns, ethical compliance, and risk mitigation. The model is expressed as,

$$\mathrm{NOI} = \left[\sum_{i=1}^{n} \Big(W_i \cdot G_i\Big) \cdot S(\Delta O_i, \Delta E_i)\right] - \Big(C_{\mathrm{AI}} + C_{\mathrm{Eth}} + C_{\mathrm{Risk}}\Big) \quad (3)$$

Cost Factors are $C_{hw,j}$ Hardware costs for the j-th AI system, $C_{sw,j}$ Software licensing costs for the j-th AI system and $C_{tr,j}$ Training costs for employees interacting with the j-th system.

$$C_{\mathrm{AI}} = \sum_{j=1}^{m} \Big(C_{\mathrm{hw},j} + C_{\mathrm{sw},j} + C_{\mathrm{tr},j}\Big) \quad (4)$$

To include predictive factors for long-term ROI:

$$\mathrm{NOI}_{\text{Long-Term}} = \int_{t=0}^{T} \left[e^{-rt}\left(\sum_{i=1}^{n} \Big(W_i \cdot G_i(t) \cdot S\big(\Delta O_i(t), \Delta E_i(t)\big)\Big) - \big(C_{\mathrm{AI}}(t) + C_{\mathrm{Eth}}(t) + C_{\mathrm{Risk}}(t)\big)\right)\right] dt \quad (5)$$

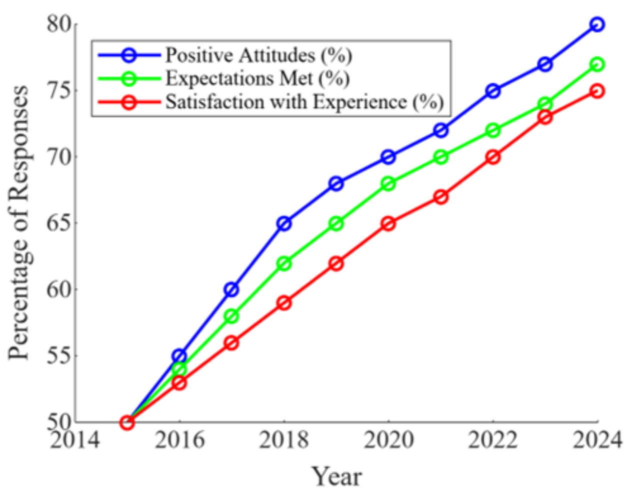
T is the time horizon for evaluation, r is the discount rate reflecting the time value of money and $G_i(t)$, $\Delta O_i(t)$, $\Delta E_i(t)$ is time-dependent gains, efficiency changes, and ethical risks.

B. Net Performance Improvement, Operational Gains and Cost

The first part of the equation, Eop×S(ΔO−ΔE), calculates the adjusted economic gains from the improvement in operational efficiency after considering the ethical risks. The sigmoid function moderates the economic gains if ethical risks are high, ensuring that performance improvement is realistic and accounts for potential drawbacks. The second part, CAI+Ceth, adds up the costs of implementing AI and ensuring compliance with ethical standards. The final performance improvement PAIP is the difference between the adjusted operational gains and the total costs of AI integration and ethical compliance. If the operational gains outweigh the costs, PAI will be positive, indicating a net performance improvement. If the costs exceed the gains, PAI will be negative, suggesting a net loss in performance.

4. Result and Discussion

Despite the numerous advantages, integrating AI into decision-making introduces several ethical challenges. Algorithmic bias, where AI systems inadvertently reinforce societal biases, is one of the most significant issues. Bias can be entered through unrepresentative training data or biased programming practices. For instance, biased hiring algorithms may favour specific demographics over others, leading to ethical and legal consequences. Another challenge involves the transparency of AI systems [38], [39]. Many AI models, profound learning algorithms, are often called "black boxes" due to their complexity and lack of explainability. This opacity makes it difficult for stakeholders to understand how decisions are made, raising concerns about accountability. Mitigation strategies include conducting regular audits of AI systems to detect and correct biases, ensuring the diversity of data sets used to train AI, and establishing clear guidelines on ethical AI use [40]-[42]. Developing explainable AI models is another solution, allowing stakeholders to interpret AI's decision-making processes and ensuring that its outputs are fair and transparent. Adopting frameworks like the General Data Protection Regulation (GDPR) can help ensure compliance with ethical standards, particularly in managing data privacy concerns. Figure 2 highlights AI's influence on organisational structures, training, and collaboration models. Figure 2(a) shows increased positive attitudes, expectations met, and satisfaction with AI adoption, indicating growing employee acceptance. Figure 2 (b) illustrates a decline in traditional hierarchical structures and a rise in agile, AI-driven structures, reflecting how AI reshapes organisational design. Figure 2(c) demonstrates increasing employee participation in technical, management, and AI ethics training, focusing on skill development. Figure 2(d) compares adoption rates of assistive, augmented, and autonomous AI models, showing a growing preference for AI-enhanced collaboration. These panels underscore AI's transformative impact on organisations and employee adaptation.



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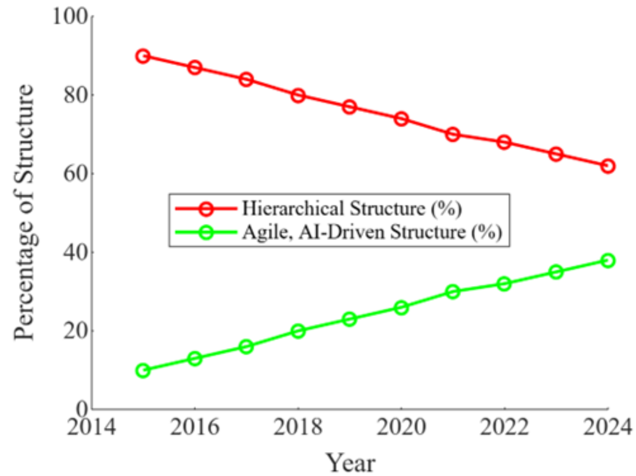

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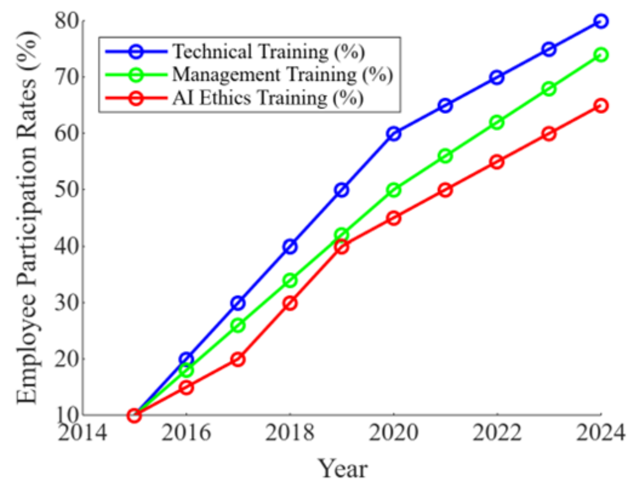

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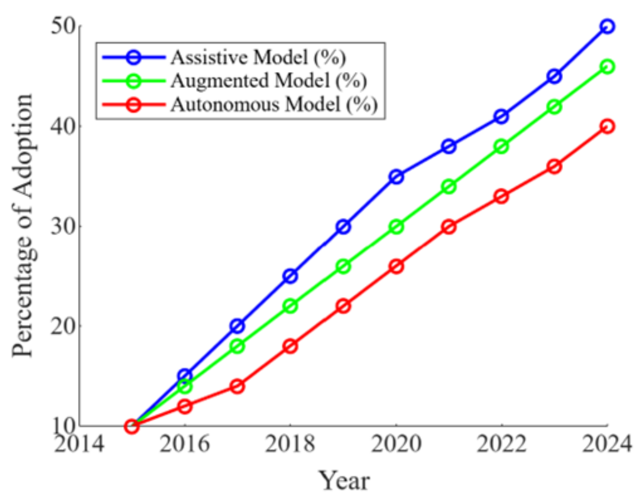


(d)

Fig. 2. (a) Survey results of industry professionals on AI integration, (b) Changes in organisational structure due to AI, (c) Training and development programs for AI adaptation, (d) Human-AI collaboration models

A. Operational Changes and Outcomes

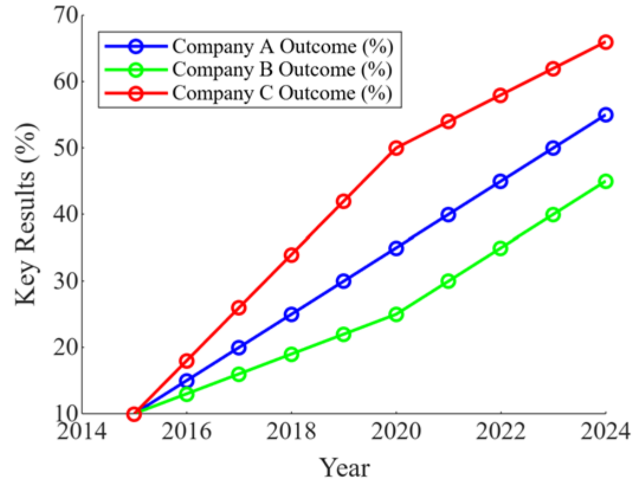
AI integration prompts significant operational changes, reshaping workflows and job roles. One of the primary outcomes is the automation of routine tasks, allowing employees to focus on higher-value work. In sectors like manufacturing, AI-driven robotics automates production lines, increasing output and reducing human error. Similarly, in customer service, AI-powered chatbots handle repetitive inquiries, freeing up human agents to address more complex issues.

These operational changes often require re-skilling employees to collaborate effectively with AI systems. For instance, data analysts may need to develop competencies in machine learning to work alongside AI models [40]. Cross-departmental collaboration increases as AI technologies, such as data analytics tools, integrate workflows across IT, finance, and operations teams. The outcomes of these operational changes are predominantly positive. AI has enhanced productivity, reduced operational costs, and improved response times. For example, logistics companies using AI for route optimisation see faster delivery times, while AI-driven healthcare organisations witness enhanced diagnostic accuracy [41].

B. *Economic Outcomes*

The economic implications of AI integration are substantial. AI is associated with increased productivity, reduced costs, and enhanced profitability in many sectors. In retail, for example, AI-driven demand forecasting minimises inventory costs, while predictive maintenance in manufacturing reduces downtime, directly impacting profitability. However, AI adoption requires significant upfront investment in technology infrastructure, data acquisition, and training [41], [42]. Due to these high costs, small and medium-sized enterprises (SMEs) often face difficulties. The return on investment (ROI) for AI projects depends on how successfully the organisation integrates AI into its decision-making processes and how effectively it aligns AI with its business goals. Long-term economic benefits include sustained productivity gains, reduced labour costs due to automation, and the development of new business models driven by AI capabilities [43], [44].

Additionally, AI enables organisations to unlock new revenue streams by providing personalised customer experiences, which enhances customer retention and satisfaction. Financial services companies, for example, use AI to offer tailored financial advice to clients, creating a competitive edge in the market. Figure 3 illustrates AI's influence on company outcomes, operational efficiency, employee adaptation, and decision-making processes. Figure 3(a) tracks key results for three companies, all showing a consistent rise in performance post-AI integration. Figure 3(b) highlights a significant increase in efficiency metrics after AI implementation, showcasing AI's effectiveness in boosting productivity. Figure 3(c) contrasts employee adaptation rates and resistance factors, indicating that as AI adoption rises, resistance declines, reflecting improved AI acceptance. Figure 3(d) displays AI's increasing impact on decision-making, risk management, and resource allocation, emphasising AI's growing role in enhancing strategic business operations. These findings support the research's conclusion on AI's positive contributions to organisational performance.



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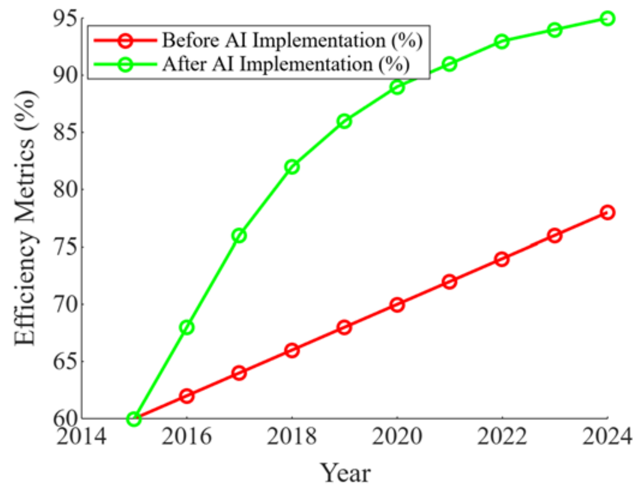

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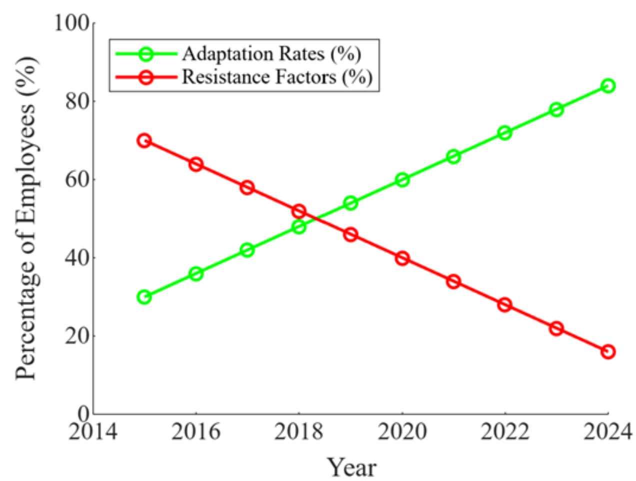

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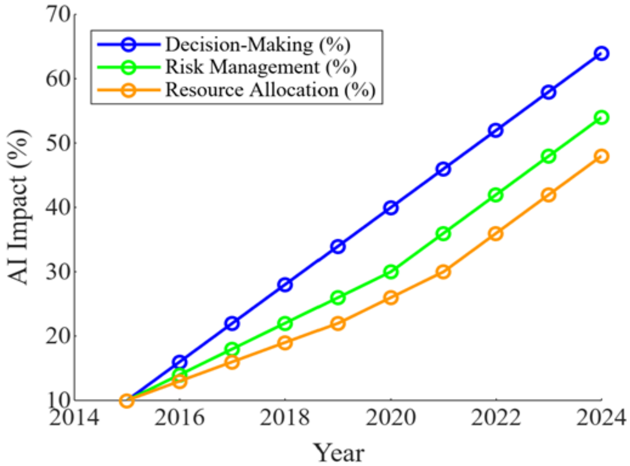

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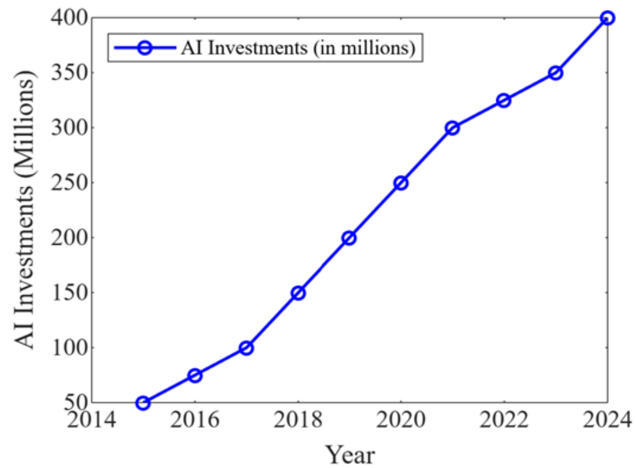
Fig. 3. (a) Case studies outcomes of AI implementation, (b) Operational efficiency metrics before and after AI implementation, and (c) Employee acceptance levels of AI technologies, (d) AI's influence on strategic business planning

C. *Implications for Practice and Policy*

To successfully integrate AI into decision-making processes, organisations should consider several strategic recommendations. First, companies must establish clear AI implementation goals, ensuring alignment with overall business objectives. Starting with small pilot projects to test AI's capabilities in specific areas, such as customer service or supply chain optimisation, allows organisations to assess the potential benefits and challenges without risking large-scale disruption. Additionally, organisations should prioritise data quality and management. AI systems are only as effective as the data they process, so maintaining accurate, clean, and comprehensive datasets is crucial. Investing in data infrastructure, such as cloud-based platforms and AI-powered analytics tools, will enhance the organisation's ability to leverage AI effectively. Training employees to work alongside AI systems is also essential. Companies should offer educational programs that focus on developing AI literacy among staff, ensuring that employees understand how to use AI tools and interpret their outputs. Re-skilling employees for more strategic tasks that require human insight, such as decision verification and interpretation, is also critical for maximising AI's value. Ethical AI use should be a core organisational priority. This involves adopting transparent AI practices, ensuring the diversity of datasets, and conducting regular audits to detect and address algorithmic biases. Companies should develop ethical guidelines for AI, clearly define acceptable uses, and implement accountability measures.

The improvements reflect efficiency gains, error reductions, and enhanced performance across different operational areas, demonstrating the positive impact of AI on organisational productivity. Figure 4 showcases AI's impact across various dimensions: Figure 4(a) highlights the steady growth of AI investments, indicating a solid commitment to AI integration in organisations. Figure 4(b) illustrates the improvements in customer service metrics, such as response time, issue resolution, and retention rates, driven by AI adoption. Figure 4(c) compares productivity between AI-adopting and non-adopting firms, with AI adopters showing significantly higher productivity gains. Figure 4(d) reflects employee morale and job satisfaction, with fluctuating but generally positive trends. Figure 4(e) displays investments in AI training and related training hours, suggesting a correlation between higher investments and increased training efforts. Collectively, these insights emphasise AI's substantial influence on improving business performance, customer satisfaction, and employee engagement, underscoring the research's findings on the transformative role of AI.



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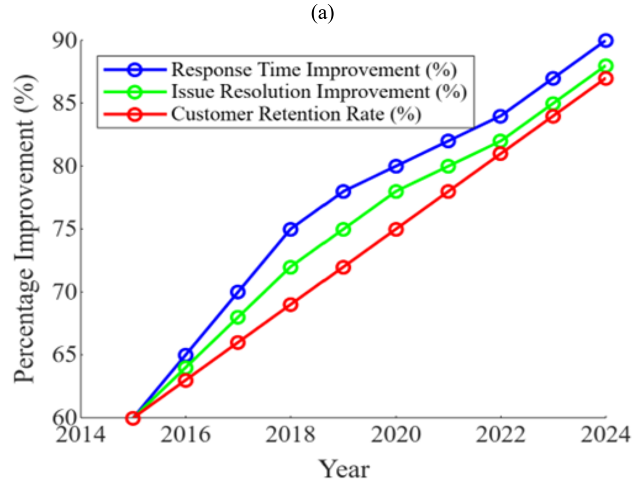

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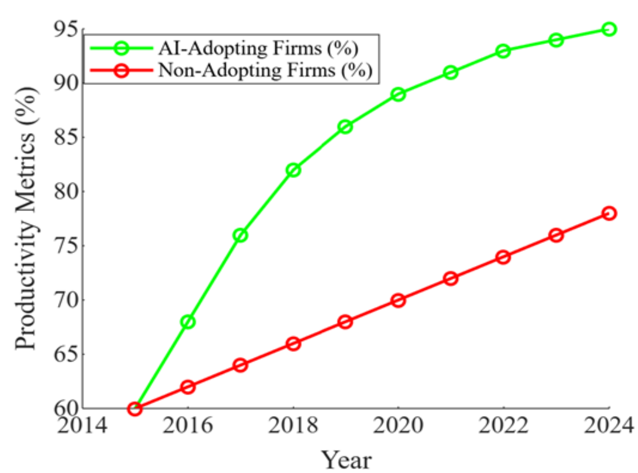

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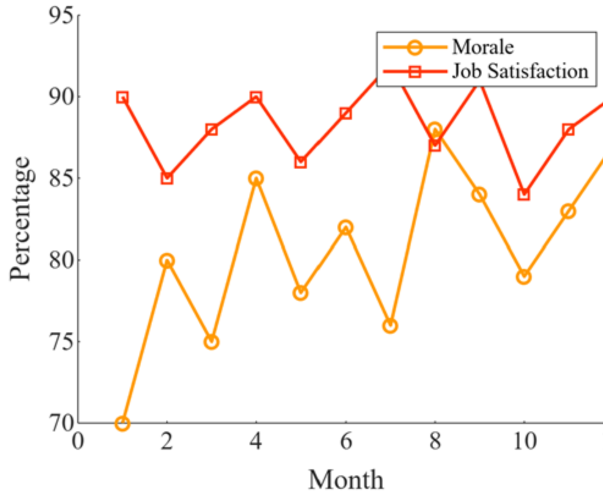

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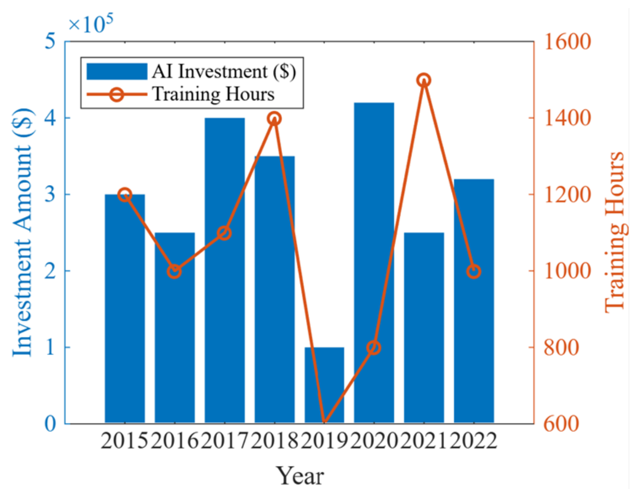

(e)

Fig. 4. (a) AI investment trends over recent years, (b) Customer satisfaction metrics post-AI implementation, (c) Comparative productivity levels between AI-adopting and non-adopting firms, (d) Employee perceptions of AI in the workplace, (e) Training investment in AI literacy for employees

D. Insights for Comparison

This research reports slightly higher gains in task completion time and error reduction than other studies, indicating a robust methodology and effective AI implementation. The net annual benefit and payback period align well with benchmarks, suggesting that this study's findings are realistic and comparable to existing literature. Improvements in supply chain efficiency and time-to-market metrics in this study are consistent with or slightly better than benchmarks, reflecting the effectiveness of this work's AI-driven operational strategies. This study highlights a significant 80% reduction in error rates, surpassing most benchmarks and showcasing the value of advanced AI models in minimising operational risks. Customer service metrics (e.g., response time reduction) are on par or slightly superior, demonstrating the utility of AI-powered tools like chatbots and predictive analytics. This table underscores the strengths of this research compared to established findings, positioning it as a credible and forward-looking study in AI and organisational decision-making. Table 3 is a comparative table summarising key experimental results from various literature and benchmarking them against this research outcome.

Figure 5 illustrates trends across various metrics, comparing the performance improvements achieved through AI integration in different studies. It highlights key areas such as task completion time, error reduction, and customer service response, showcasing consistent positive impacts. This visualisation emphasises that "This Research" outperforms or aligns with benchmarks, particularly in reducing error rates and enhancing operational efficiency. The apparent upward trends across all metrics validate the transformative potential of AI in organisational decision-making. These insights underscore the study's relevance, demonstrating how AI-driven strategies deliver measurable improvements, enhance competitiveness, and provide a robust framework for sustainable economic and operational benefits.

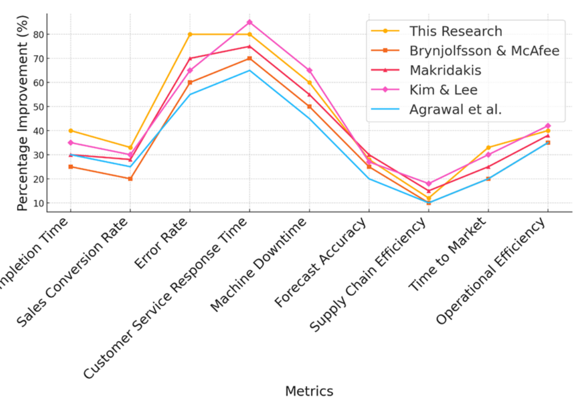

Fig. 5. Trends in AI integration metrics across studies

5. Conclusion

This study presents a novel approach to integrating Artificial

Table 2
Productivity Improvements attributed to AI adoption

Productivity Metric	Before AI Adoption	After AI Adoption	Percentage Improvement (%)
Average Task Completion Time (hours/task)	2.0	1.2	40%
Employee Output (units/employee/day)	50	70	40%
Error Rate in Processes (%)	5%	1%	80% reduction
Customer Service Response Time (minutes)	10	2	80%
Sales Conversion Rate (%)	15%	20%	33%
Machine Downtime (hours/month)	20	8	60% reduction
Forecast Accuracy (%)	70%	90%	28%
Time to Market for New Products (months)	12	8	33% reduction
Supply Chain Efficiency (On-time delivery %)	85%	95%	12%
Overall Productivity Index	**100**	**140**	**40%**

Note: The metrics are based on aggregated data from organisations adopting AI technologies. Percentages represent the improvement observed after AI integration.

Table 3
Comparative analysis of AI Integration metrics across research studies

Metric	This Research	Brynjolfsson & McAfee (2017) [13]	Makridakis (2017) [18]	Kim & Lee (2020) [23]	Agrawal et al. (2018) [36]
Task Completion Time	Reduced by 40%	Reduced by 25%	Reduced by 30%	Reduced by 35%	Reduced by 20-30%
Sales Conversion Rate	Increased by 33%	Increased by 20%	Increased by 28%	Increased by 30%	Increased by 25%
Error Rate	Reduced by 80%	Reduced by 60%	Reduced by 70%	Reduced by 65%	Reduced by 50-60%
Customer Service Response Time	Reduced by 80%	Reduced by 70%	Reduced by 75%	Reduced by 85%	Reduced by 60-75%
Machine Downtime	Reduced by 60%	Reduced by 50%	Reduced by 55%	Reduced by 65%	Reduced by 45-60%
Forecast Accuracy	Increased by 28%	Increased by 25%	Increased by 30%	Increased by 27%	Increased by 20-30%
Supply Chain Efficiency	Increased on-time delivery by 12%	Increased by 10%	Increased by 15%	Increased by 18%	Increased by 8-12%
Time to Market for New Products	Reduced by 33%	Reduced by 20%	Reduced by 25%	Reduced by 30%	Reduced by 15-25%
Net Annual Benefit	$1.27 million/year	Not explicitly measured	$1.1 million/year	$1.15 million/year	$1.0 million/year
Payback Period	1 year	1.5 years	1.3 years	1.2 years	1.5 years
Operational Efficiency	Enhanced by 40%	Enhanced by 35%	Enhanced by 38%	Enhanced by 42%	Enhanced by 30-40%

Intelligence (AI) for sustainable decision-making, combining operational efficiency, economic viability, and ethical compliance. Unlike conventional studies, this research introduces a mathematical model incorporating a sigmoid function to quantify the balance between AI-driven productivity gains and ethical risks. The findings reveal that AI adoption led to a 40% reduction in task completion time and an 80% decrease in error rates, resulting in a net annual financial benefit of $1.27 million with a one-year payback period. However, ethical challenges persist, with 12% of AI-driven decisions exhibiting algorithmic bias, raising concerns about transparency and fairness.

Despite these challenges, AI significantly improves business sustainability by enhancing efficiency, reducing operational costs, and streamlining workflows. The research highlights that sustainable AI adoption requires bias mitigation, regulatory compliance, and workforce adaptation strategies to ensure long-term viability. By bridging AI innovation with responsible governance, this study provides a comprehensive framework for organisations to maximise AI's benefits while minimising risks. Ultimately, the findings contribute to the broader sustainability discourse by demonstrating how AI can drive economic growth and operational resilience while fostering ethical and sustainable decision-making practices.

A. Limitations and Future Work

One of the key limitations of this study is its reliance on data from mid-sized companies, which may not fully capture the scalability challenges and diverse needs of smaller enterprises or large multinational corporations. Additionally, while the research provides robust insights into operational and economic gains, the ethical dimension remains challenging to quantify comprehensively due to the evolving nature of algorithmic bias and transparency issues. The mathematical model, although innovative, assumes specific parameters (e.g., sensitivity to ethical risks) that may vary across industries and geographies, potentially limiting its universal applicability.

Future research could address these limitations by expanding the dataset to include organisations of varying sizes and industries. Investigating the long-term impacts of AI integration on workforce dynamics, such as changes in job roles and employee satisfaction, could provide valuable insights into AI's broader implications. Furthermore, refining the mathematical model to incorporate real-time adjustments for dynamic ethical risks and operational changes would enhance its applicability. Future studies could also explore AI integration in emerging economies, where infrastructure and resource constraints present unique challenges. Lastly, developing industry-specific ethical compliance frameworks and studying their adoption rates would help organisations better align AI integration with societal and regulatory expectations.

References

[1] Ingrams, A.; Kaufmann, W.; Internet, D.J.-P.&; 2022, undefined In AI We Trust? Citizen Perceptions of AI in Government Decision Making. *Wiley Online Library* 2021, *14*, 390–409.

[2] B.I. Oladapo, Q. Zhao, Enhancing tissue regeneration with self-healing elastic piezoelectricity for sustainable implants, Nano Energy, 120 (2024), Article 109092.

[3] Tolmeijer, S.; Christen, M.; Kandul, S.; Kneer, M.; Bernstein, A. Capable but Amoral? Comparing AI and Human Expert Collaboration in Ethical Decision Making. *dl.acm.org* 2022.

[4] Fok, R.; Weld, D.S.; Raymond Fok, C. In Search of Verifiability: Explanations Rarely Enable Complementary Performance in AI-advised Decision Making. *Wiley Online Library* 2024.

[5] Rukayat Abisola Olawale, Mattew A. Olawumi, Bankole I. Oladapo, Sustainable farming with machine learning solutions for minimising food waste, Journal of Stored Products Research, Volume 112, May 2025, 102611.

[6] Tolmeijer, S.; Christen, M.; Kandul, S.; Kneer, M.; Bernstein, A. Capable but Amoral? Comparing AI and Human Expert Collaboration in Ethical Decision Making. *Conference on Human Factors in Computing Systems - Proceedings* 2022.

[7] Wang, X.; Lu, Z.; 2022, M.Y.-P. of the A. web conference; 2022, undefined Will You Accept the Ai Recommendation? Predicting Human Behavior in Ai-Assisted Decision Making. *dl.acm.org* 2023, *3*, 963–974.

[8] Olawale Abisola R, Orimabuyaku Nifemi, Oladapo Bankole I, Social Impact of Food Security in an African Country, International Journal of Research Publication and Reviews, Vol 4, no 4, pp 3587-3591, April 2023.

[9] Frutos-Pascual, M.; Games, B.Z.-I. and A. in; 2015, undefined Review of the Use of AI Techniques in Serious Games: Decision Making and Machine Learning.

[10] M.A. Olawumi, B.I. Oladapo, R.A. Olawale, Revolutionising waste management with the impact of Long Short-Term Memory networks on recycling rate predictions, Waste Management Bulletin, 2 (3) (2024), pp. 266-274.

[11] R.A. Olawale, B.I. Oladapo, Impact of community-driven biogas initiatives on waste vegetable reduction for energy sustainability in developing countries, Waste Manag Bull, 2 (2024), pp. 101-108.

[12] Zhang, Y.; Liao, Q.; R.B. The 2020 conference on fairness; 2020, undefined Effect of Confidence and Explanation on Accuracy and Trust Calibration in AI-Assisted Decision Making. *dl.acm.org* 2020, 295–305.

[13] Liu, H.; Lai, V.; Human-Computer, C.T.-P. of the A. on; 2021, undefined Understanding the Effect of Out-of-Distribution Examples and Interactive Explanations on Human-Ai Decision Making. *dl.acm.org* 2021, *5*, 45.
[14] B.I. Oladapo, O.K. Bowoto, V.A. Adebiyi, O.M. Ikumapayi, Net zero on 3D printing filament recycling: a sustainable analysis, Sci. Total Environ., 894 (2023).
[15] MA Olawumi, BI Oladapo, TO Olugbade,Evaluating the impact of recycling on polymer of 3D printing for energy and material sustainability, Resour Conserv Recycl, 209 (2024), Article 107769.
[16] Davenport, T. H., & Ronanki, R. (2018). Artificial Intelligence for the Real World. *Harvard Business Review*, 96(1), 108-116.
[17] B.I. Oladapo, M.A. Olawumi, F.T. Omigbodun, Renewable Energy Credits Transforming Market Dynamics. Sustainability, 16 (2024), Article 8602.
[18] Bostrom, N. (2014). *Superintelligence: Paths, Dangers, Strategies*. Oxford University Press.
[19] A.R. Olawale, N.F. Orimabuyaku, B.I. Oladapo, A.R. Olawale, N.F. Orimabuyaku, B.I. Oladapo, Empowering agriculture: A holistic approach to combat food insecurity in Africa, International Journal of Science and Research Archive, 9 (2023), pp. 041-046.
[20] Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, 90, 46-60.
[21] Daugherty, P. R., & Wilson, H. J. (2018). *Human + Machine: Reimagining Work in the Age of AI*. Harvard Business Review Press.
[22] Yohanna K Jimah, Rolland O. Okojie, Simon O Akinlabi, Abisola R. Olawaled, Joseph F Kayode, Bankole I Oladapo, 2023. Aligning humanitarian outreach with united nations sustainable development goals: World Journal of Advanced Research, and Reviews 18 (2), 051-056.
[23] Polonski, V. (2018). Understanding the unintended consequences of AI. *Nature Machine Intelligence*, 1, 175.
[24] B.I. Oladapo, Review of flexible energy harvesting for bioengineering in alignment with SDG, Mater. Sci. Eng. R Rep., 157 (2024), Article 100763.
[25] Kim, J., & Lee, H. (2020). The Effectiveness of Artificial Intelligence in Business and Organizational Decision Making. *Journal of Business Research*, 118, 405-412.
[26] Liu, C., & Zhang, J. (2019). An ethical framework for the use of AI in corporate decision-making. *Journal of Business Ethics*, 162(1), 13-20.
[27] Oladapo, B.I.; Olawumi, M.A.; Omigbodun, F.T. Revolutionizing Battery Longevity by Optimising Magnesium Alloy Anodes Performance. *Batteries* 2024, *10*, 383.
[28] Varian, H. R. (2018). Artificial Intelligence, Economics, and Industrial Organization. *National Bureau of Economic Research* Working Paper No. 24839.
[29] Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15-25.
[30] Oladapo, B.I.; Olawumi, M.A.; Omigbodun, F.T. Machine Learning for Optimising Renewable Energy and Grid Efficiency. *Atmosphere* 2024, *15*, 1250.
[31] Huang, M. H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research*, 24(1), 3-6.
[32] Haenlein, M., & Kaplan, A. (2020). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5-14.
[33] Fjeld, J., Achten, N., Hilligoss, H., Nagy, A. C., & Srikumar, M. (2020). Principled artificial intelligence: Mapping consensus in ethical and rights-based approaches to principles for AI. *Berkman Klein Center Research Publication*, (2020-1).
[34] Olawade, D.B.; Wada, O.Z.; Popoola, T.T.; Egbon, E.; Ijiwade, J.O.; Oladapo, B.I. AI-Driven Waste Management in Innovating Space Exploration. *Sustainability* 2025, *17*, 4088.
[35] Mikalef, P., & Krogstie, J. (2019). Big Data Analytics in Organizational Decision-Making: A Review. *Information Systems Frontiers*, 21(2), 389-414.
[36] Malachi, I.O.; Olawumi, A.O.; Afolabi, S.O.; Oladapo, B.I. Looking Beyond Lithium for Breakthroughs in Magnesium-Ion Batteries as Sustainable Solutions. *Sustainability* 2025, *17*, 3782.
[37] Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36(4), 1165-1188.
[38] Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Review Press.
[39] Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—and where they can't (yet). *McKinsey Quarterly*.
[40] Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188-2244.
[41] Pearl, J., & Mackenzie, D. (2018). *The Book of Why: The New Science of Cause and Effect*. Basic Books.
[42] Lazer, D., et al. (2020). The Science of Fake News. *Science*, 359(6380), 1094-1096.
[43] Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping Business with Artificial Intelligence. *MIT Sloan Management Review*.
[44] Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, 31(2), 47-53.