AI Integration in Scientific and Clinical Research Management: Cost Reduction, Decision-Making and Leadership

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Abstract. This essay investigates whether artificial intelligence can help the management department to reduce costs and decision-making within scientific and clinical research organizations. The research subject is mainly scientific and clinical research organizations, with the specific case study of Thermo Fisher Scientific. This case study examines the real-life application of AI within the company, showing AI's ability to increase productivity, reduce costs, improve decision-making, and change leadership style. Looking into the recent literature, the essay discussed how AI such as Machine Learning and Deep Learning is implicated in the scientific and clinical field. Key challenges include high upfront costs, lack of technology experts, and concerns about data privacy. This essay concludes by providing possible solutions to cope with these challenges, which include AI training in labor, further research data on AI implementation in the real world and strict regulation on AI data privacy.

Keywords: artificial intelligence, machine learning, Artificial intelligence labor training

1. INSTRUCTION

Artificial Intelligence (AI) refers to computer systems designed to mimic human cognitive functions like learning, reasoning, and problem-solving. It encompasses technologies that leverage algorithms and data-driven decision-making to address intricate challenges traditionally requiring human intellect. As AI applications grow increasingly pervasive across industries, they are reshaping how we work and live—particularly in the business world. Businesses today leverage AI in diverse sectors and use cases, unlocking new opportunities to elevate their chances of success. When implemented strategically, AI becomes a transformative tool, enhancing operational efficiency and driving higher success rates across roles and processes.

AI technology focuses on enabling systems to perceive, interpret, and act intelligently. Modern advancements in information science are accelerating due to robust AI infrastructure, which includes core components such as data management, storage solutions, computational resources, machine learning algorithms, and specialized AI frameworks. The perception layer, similar to the human brain, deals with recognizing and interpreting raw data. It equips machines with fundamental sensory capabilities: computer vision grants systems the ability to analyze visual inputs, while speech processing technologies enable auditory recognition and vocal output (Agrawal, 2023). The cognitive layer focuses on understanding and processing text data through tools like natural language processing (for linguistic understanding), knowledge graphs (for structured information mapping), and adaptive learning systems (Tejeda, 2022). At the decision-making layer, AI leverages automated planning, expert systems, and decision-support mechanisms to generate optimized actions or solutions. Together, these layers form a cohesive structure that drives AI's ability to emulate and augment human-like intelligence (Nadkarni, 2011).

2. Literature Review

In the past 20 years, Artificial Intelligence has experienced rapid development and progress, gradually transforming from only theoretical thoughts into real-life practice. This development has affected various industries and organizations, from scientific and clinical fields to business management, there has been a significant increase in the use of AI technology (Gao, 2024).

AI processes vast datasets to uncover patterns, enabling predictive analytics and real-time adjustments across sectors such as healthcare and retail. In the era of big data—defined by its high variety, immense volume, and rapid velocity, traditional statistical methods often fail to efficiently process information or derive actionable insights. Artificial intelligence (AI), by contrast, thrives in this environment, identifying subtle patterns and complex relationships that conventional analytical techniques struggle to detect. The transformative power of AI is particularly evident in genetics. A key challenge in this field involves determining the clinical significance of single amino acid polymorphisms (genetic variants). Early approaches, such as SIFT (a sequence conservation-based method) and SySAP (a network-driven model), encountered limitations in predictive accuracy. To overcome these barriers, Sundaram et al. developed Primate AI, a deep neural network (DNN) tool that outperforms predecessors by more accurately predicting the harmful effects of genetic mutations (Sundaram, 2018). By harnessing AI's ability to analyze vast, multidimensional datasets, Primate AI enhances precision in genetic diagnostics and research. This advancement underscores AI's capacity to transcend the constraints of older methodologies, offering scalable solutions tailored to the demands of modern big data. In automation, it streamlines repetitive tasks, reduces errors, and frees resources for more complex work, with applications in robotic process automation and industrial optimization. For decision-making, AI offers data-driven recommendations that aid in risk management and strategic planning, while ethical considerations like bias mitigation and transparency ensure alignment with organizational values.

2.1. AI in Scientific Research

In the field of scientific research, AI coping with Machine Learning (ML) and Deep Learning (DL) has an impact on a variety of disciplines, including Mathematics, Material Science, Geoscience, Physics, Chemistry, and medical science (Xu, 2021). ML is a subset of AI, which the systems are set up by using algorithms, so they are able to learn and improve their performance on assignments through practice and data, without manual definitive programming (Janiesch, 2021). DL, a subset of ML, has the capability to model extremely complex patterns. DL uses deep neural networks that aim to mimic how the human brain functions. In Mathematics, ML can help with solving extremely difficult functions even with partial differential problems. ML and DL in Material Sciences, not only help with discovering new materials but also manufacturing. AI is able to access and analyze large amounts of geo-data more efficiently than humans, making it much more effective for geologists to find solutions for the upcoming environmental threats. ML is used in all scales of physics, from partial physics to cosmic physics, helping scientists from understanding atoms and molecules to discover and monitor the movement of stars and galaxies. In chemistry, AI mostly works on experiments, including creating hypotheses, experiment routes, and obtaining more accurate results. Moreover, AI doctors can evaluate patient's medical history and give possible treatments.

AI also played an important role in drug discovery. Traditionally, developing a new drug has taken around 10 years and over a billion dollars. Accelerating drug discovery and avoiding late-stage failures are critical goals for major pharmaceutical companies. AI, including machine learning, deep learning, expert systems, and artificial neural networks, has introduced new insights and improved efficiency in drug discovery. It is used in designing new molecules, modeling proteins and ligands, researching quantitative structure-activity relationships, and assessing druggable properties. Deep learning-based AI tools are particularly effective in tackling complex challenges in drug discovery. Additionally, predicting chemical synthesis routes and optimizing processes help speed up discovery and reduce production costs. Recent advancements in AI-assisted drug discovery have been remarkable, especially in identifying new chemical entities and related business sectors. DeepMind's AlphaFold platform, which utilizes deep neural networks to predict 3D protein structures, has surpassed other algorithms in performance. Impressively, AlphaFold accurately predicted 25 novel protein structures from a panel of 43 without using pre-existing models. As a result, AlphaFold won the CASP13 protein folding competition in December 2018 (AlQuraishi, 2019).

2.2. AI in the clinical field

In the field of clinical and healthcare sector, the application of AI is also remarkable. Diagnosis is the main application of AI in the clinical field. The multi-model that combines medical imaging and electronic health records (EHR) with AI has shown high accuracy in diagnosing diseases, with mainly diagnosis of neurological disorders. ML and DL are also commonly used in this case, with ML slightly more popular than DL (Mohsen, 2022). Prediction tasks, such as disease prediction, mortality prediction, and treatment outcome prediction can also be generated by AI. AI has also demonstrated its strong potential in predicting possible future injuries patients may face. Recently, by analyzing athletes' clinical history and personal body indicators, the ML algorithm has proved its ability to predict future injury with very high accuracy (Ramkumar, 2021). Simple and redundant tasks can be completed by AI, such as patient care coordination and common documentation, this saves time for healthcare providers and allows them to focus on more important patient-facing work. If patients are unable to meet face to face, AI can remotely access the patient's condition and telemedicine. For large data sets that if manually analyzed have low efficiency and will waste a lot of human resources, AI in this case can help to analyze and generate decision-making. However, it is sometimes misunderstood that thinking the application of AI can replace doctors and healthcare providers, AI is only generated as a helpful tool for physicians to improve their efficiency and capability.

2.3. Gaps in literature

Despite the large amount of research in scientific and clinical fields, there are still gaps that recent research has not discussed. AI has been discussed within a variety of disciplines, however, there is only a little research that discusses it in an interdisciplinary view. In order to use AI to its full potential, future models and research can focus on the interdisciplinary characteristics of AI, combining different fields together. Some research also points out that multi-model performs better than single modality models in the clinical field, but there aren't enough multi-models that is developed and researched on, it is still much to explore. Furthermore, one main limitation that AI applications in clinical and scientific fields is ethics and regulation. As developed rapidly in the past two decades, ethical frameworks for AI application in clinical and scientific research are not yet refined and widely known. More regulatory policies should be established to ensure AI reaches its maximum potential while also following the ethical fundamentals in research (Foote, 2025).

3. Methodology

3.1. Case study: Thermo Fisher Scientific

Thermo Fisher Scientific is a global leader in advancing scientific research and innovation, providing a comprehensive portfolio of products and services that include scientific instrumentation, essential consumables and reagents, advanced software solutions, and specialized laboratory support. The company serves a diverse range of sectors, including life sciences, healthcare, biotechnology, pharmaceuticals, and academic, governmental, and industrial laboratories. By equipping researchers, clinicians, and industry professionals with cutting-edge tools and technologies, Thermo Fisher Scientific empowers advancements in discovery, diagnostics, and operational efficiency across global scientific communities (Thermo Fisher Scientific, 2025).

Thermo Fisher, as a clinical and scientific research behemoth, is prominent in the fields of life science, healthcare, and technology. Fisher would be an ideal case study to evaluate AI applications in scientific fields, as well as AI's impact on management. Looking into the implication and influence of AI integration in Thermo Fisher, allows researchers to understand how AI is generated in real life in research and business, not only theoretical thoughts and identifying the affectedness of different models.

The company operates through four core segments: Life Sciences Solutions, which provides reagents, PCR technologies, and bioprocessing tools; Analytical Instruments, offering advanced equipment such as mass spectrometers and electron microscopes; Specialty Diagnostics, specializing in clinical testing and immunoassays; and Laboratory Products & Services, delivering lab equipment distribution and contract development/manufacturing (CDMO) solutions through subsidiaries like Patheon (Allen, 2014). Strategic acquisitions, including Life Technologies, FEI Company, and Patheon, have bolstered its capabilities in genomics, microscopy, and pharmaceutical production. Committed to its mission of enabling a healthier, cleaner, and safer world, Thermo Fisher supports drug development, precision medicine, and critical diagnostics, with significant contributions during the COVID-19 pandemic through testing supplies and vaccine manufacturing support. Generating over $40 billion in annual revenue (as of 2023) and consistently ranking among the Fortune 500, the company remains a cornerstone of scientific advancement, serving academic, industrial, and healthcare sectors globally.

3.2. AI applications in the company

The life science sector is undergoing significant transformation through the integration of artificial intelligence (AI), particularly in areas such as drug discovery, imaging diagnostics, drug development, and precision medicine. Thermo Fisher Scientific, a leading organization in this field, represents a strategic focus for AI implementation due to its involvement in genome sequencing, gene-clinical outcome relationship mapping, and phenotype data analysis. Traditional rule-based systems are insufficient for analyzing the human genome's 3 billion nucleotides, but AI and machine learning (ML) have already proven effective in enhancing disease prediction, drug design, and diagnostic accuracy (Shrestha, 2019).

Thermo Fisher's software infrastructure supports advanced digital technologies, including AI, to accelerate scientific innovation. This positions its R&D department as an ideal case study for examining AI's role in fostering innovation and leadership. We selected a single-case study design, which aligns with inductive, exploratory research. This approach enables an in-depth examination of a unique context—a pioneering life science organization yet to integrate AI into critical functions. Through interviews with R&D personnel, we aim to uncover barriers, opportunities, and strategic pathways for adoption of AI, addressing current gaps and aligning with sector-wide advancements (Marshall, 2017).

3.3. AI influences the company

Overall, the implication of AI at Thermo Fisher Scientific has largely impacted their managerial performance and leadership development, especially from the perspective of cost, productivity, decision-making, and leadership style.

One of the most important successes of AI implementation at Thermo Fisher Scientific is the increase in productivity and reduction in cost. The application of AI can reduce the time taken for various processes and expedite the project process, by using the correct AI tools, simple and repeat tasks such as data entry, sample analysis, and experimental reporting that have previously used up a lot of labor capital can be automatized. Employees specifically in technical and scientific works have noticed their change in task types from simple and mundane work to more analytical and strategic work. Also, teams using more AI-powered platforms are able to complete experiments approximately 20–30% faster than those only working manually. This automation has not only increased the productivity of the organization but also helped to reduce costs (Al-Walai, 2021). There will be reduced manual workloads, and labor costs for these tasks can be saved as AI is replacing their work. AI is able to generate more accurate results and make fewer mistakes than human labor, this would minimize waste resources and time, reduce the resources and time used to repair these mistakes, and avoid production delays. Data integrity is also improved as centralized AI systems assure data formatting consistency, safer storage, and access protocols. These improvements to the system make the company competent in cooperating, which is crucial for a global company like Thermo Fisher.

Another influence that AI has on Thermo Fisher Scientific is the reinforcement of decision-making. By the implication of AI-enabled data analytics tools such as natural language processing (NLP) tools, managers working in Thermo Fisher's now are able to access data dashboards, these dashboards present key decision indicators, predictive analytics, and simulation-based scenarios, most importantly all these information are in real-time and updated as AI are able to summarize research findings, gather and analysis data more quickly. Real-time key decision indicators increase managers' responsiveness to the market and changes; predictive analytics and simulation-based scenarios give managers the support to make proactive, rather than reactive, decisions. Moreover, AI data analytics tools are also able to identify products with high risk, this warning would assist managers to make timely strategic adjustments and reconsider before making important decisions. Thus, it helps to improve Thermo Fisher's forecasting accuracy in funding and inventory management. Another noticeable change is the trend that decision-making is shifting towards evidence-based decisions. In contrast to evidence-based decisions, intuition-driven or experience-based decisions are used very commonly before the use of AI analysis. With AI's data backup, managers are showing an increase in confidence in their decisions in project prioritization and resource allocation.

The integration of AI has also caused changes in leadership roles. Leaders at Thermo Fisher have noticed their role in becoming more adaptive, strategic, and people-focused responsibilities and AI is handling overhead to operational decision-making and data analysis tasks. Also, there are increasing needs for AI expert leaders in the company, managers and leaders are told to raise their awareness of the use of AI, they are trained to learn AI's capabilities and limitations in order to ask the right questions, interpret data-driven outputs, and make informed choices and ethnicity when using AI.

4. Challenges

Despite the many benefits that AI can bring to organizations, there are still a lot of challenges that need to be faced when implication AI. The uncertainty of return on AI investment is the main barrier to AI implication. 9% of survey participants did not gain any positive improvement after implementing AI in their organization (Paranjape, 2021). Although this is only the minority, organizations are not likely to take this risk. Financial concern is also one big challenge, AI implication requires high upfront costs. With high Upfront costs combined with uncertain gain, organizations may reject to invest in AI tools without clear and certain evidence of cost-effectiveness.

Moreover, job displacement is also one issue we can't ignore when implicating AI, a lot of employees would lose their jobs and affect the labor market. While some employees fear losing their jobs, others resist adopting new AI tools at work due to a lack of technological knowledge (Vlad Vasiliu, 2024). Especially traditional or non-technical departments would be afraid of technological complexity.

Data privacy when using AI is also a huge concern for a lot of companies. Companies are concerned that there would be leakage in sensitive patient information and confidential data when implementing AI technologies. These concerns are more intensive due to the strict data protection regulations, such as the General Data Protection Regulation (GDPR) in Europe.

5. Discussion

In order to resolve these challenges AI faces, solutions should be tackled on both the human and technological side. For the human side, the main challenge AI faces is the lack of technological knowledge and resistance to change. To deal with these two challenges, training would be the most suitable policy. When employees gain more knowledge of technology, it would be easier for them to operate and use AI tools, their workload could be decreased, and work efficiency could be increased (Lee, 2023). Training also helps with the problem of resistance to change. When employees learn how to use AI, their fear of AI complexity and change in working style will decrease, and they will be more confident in using AI and less concerned about being replaced by AI tools. With those elderly employees who are more used to traditional work, softer approaches, such as rewards and incentives should be used.

On the technological side, high upfront costs and data privacy will be the main challenges to tackle. To associate with the high upfront cost, government, and technology companies can provide financial support and subsidies for small research organizations. Also, more research can focus on the real-life improvement that AI brings to companies, clearer data will give organizations more information and willingness to take the risk of this high cost. Strict guidelines and secure data-sharing protocols on data privacy should be proposed. Moreover, to build trust between organizations and AI, transparency, fairness, and accountability should emerge in the design of AI tools. Regulation with clear guidelines on data privacy, biases, and ethics should also be established and strictly monitored.

6. Conclusion

In conclusion, this AI has caused a lot of improvement in management in scientific and clinical research organizations. Drawing from the present literature, AI technologies, especially Machine Learning (ML) and Deep Learning (DL), have been implicated in both scientific and clinical search fields, mainly in the use of data analysis and experiments. However, the current literature has lacked research on the interdisciplinary view, real-life application and ethics of AI. By evaluating this specific global scientific research organization, Thermo Fisher Scientific, this case study finds out that the company has been largely affected by applying AI to its management. AI is able to generate faster, more efficient data, thus causing improvement in productivity, reduction in costs, enhancement in decision-making and change in leadership roles in the company. There are also several obstacles implicating AI, high upfront costs, lack of technological skills among employees and concern about data privacy have hindered AI implementation in organizations. In order to expand the use of AI in more organizations, further experiment data on the real-life impact and regulation of AI should be researched to provide companies with confidence and belief in AI. Moreover, AI training for employees and government subsidies are also crucial to solving the problem.

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