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AI Optimisation vs. Human-Centric Models: An Exploratory Secondary-Data Comparative Case Study of Operational and Economic Costs in Tesla and JPMorgan Chase

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ABSTRACT

Growing changes are occurring due to the use of artificial intelligence (AI) in the operational practices of various fields, raising questions about its impact on productivity, efficiency, labour, and cost. The purpose of this study is the comparative analysis of AI-optimized and human-centred operational practices through an example of the manufacturing processes at Tesla Inc. and the financial sector activities of JPMorgan Chase & Co. The objective of this research paper is to investigate how higher use of AI affects the level of efficiency, labour usage, and other economic costs in industries that are capital-intensive and service-based. A descriptive comparative secondary-data case-study approach was used, combining quantitative analysis of company data with qualitative analysis of annual reports, regulatory filings, and other relevant sources for this study that includes quantitative analysis of the company's figures as well as qualitative analysis of their annual reports, financial and other relevant information from various industry sources. As a result of the analysis, it is revealed that the increasing technology usage in the processes at Tesla has decreased the share of labour in the operations of the company without changing the number of employees. On the contrary, JPMorgan Chase has increased investment in technologies and use of AI and the number of people working at the company. Thus, there is no definite change in the displacement of labour due to the use of AI.

KEYWORDS:
Artificial Intelligence (AI), AI Optimisation, People-Focused Approaches, Efficiency, Cost Economics, Productivity, Automation, Finance Industry.

1. INTRODUCTION

Just as numerous interconnected processes within a living organism sustain life, efficient manufacturing within a company plays a vital role in optimising productivity by enabling it to produce higher-quality products at lower costs, maximising resource utilisation, and minimising waste, time, and energy[1].

Manufacturing is the conversion of raw materials into finished products using tools, human labour, machinery, and chemical processing.[2] The higher the share of manufacturing in a country's Gross Domestic Product, the stronger its economic robustness.

While manufacturing plays a crucial role in employment, innovation, productivity, and environmental sustainability, another vital function in the company is to monitor the circulatory system, which ensures capital flows where needed and powers critical decisions from daily operations to major strategic moves[3], which is a function of financial services. Financial services are crucial to the functioning of an economy. Without them, individuals with money to save might have trouble finding those who need to borrow, and vice versa[4].

In today's technology-driven and complex environment, the effectiveness of both manufacturing and financial services depends on technological innovations and data analytics to enhance their growth. As technology continues to advance and the world becomes more digitally dependent, there is increasing pressure on firms of all sizes to ensure their buy-side operating model is as efficient as possible.[5]

AI optimisation has been a transformative change for these companies when compared to traditional human-centric approaches. However, it is worth noting that both the human-centric approach and the AI approach are subject to geopolitics, economic uncertainty and cyber insecurity. The human-centric organisation is one that revolves around the people. This organisation creates a work environment founded on trust, relationships and purpose. It fosters the basic conditions people need to thrive, providing an expert combination of empathy, support and challenge.

At the same time, artificial intelligence is significantly active in transforming the skill approach and the ethical frameworks required to achieve efficiency and productivity.[6]. AI optimisation is categorised into 3 categories:

- AI model optimisation focuses on developing AI systems themselves, making them faster and more efficient.
- AI process optimisation is useful to improve and automate various business workflows and operations.
- AI-driven optimisation involves using AI to improve specific strategies, such as enhancing website experiences or content discoverability in search.[7]

However, human-centric organisations are categorised based on their reliance on experience, Intuition, and ethical judgment. While AI-driven optimisation enhances efficiency and reduces costs. This paper examines the extent of compromise and the flexibility, along with the judgment that is inherent in human-centric models within operational and financial decision-making. This contrast can be seen in the way real-world firms adopt different AI-driven and human-centric approaches. The two companies that would be considered are Tesla and JPMorgan Chase, which epitomise the manufacturing and financial sectors with a large dependency on both AI and a human-centric approach.

The growing integration of artificial intelligence in industrial operations and in the operations of the financial sector has undergone a substantial transformation in recent years. Operational efficiency remains a critical tool in determining the competitive spirit of companies. With the AI breakout, it has become easier for firms to maximise profit by minimising operational costs. The initial ideas of AI by Alan Turing in the 1950s have evolved from simple theoretical processes to powerful real-world applications, transforming the way businesses work and shaping nearly every aspect of life itself. Financial services firms have been using AI in their processes for decades. Shortly after the advent of generative artificial intelligence (genAI), it became evident that these firms had a greater potential than most others to capitalise on advanced AI text-processing systems.[8] From the 1990s, advancements made in computational power and data processing enabled its gradual adoption, culminating in the 2010s and 2020s, when AI was being widely integrated with manufacturing operations and financial services for efficient optimisation and decision-making.

The drastic shift from theoretical use to real- life applications led companies to adopt artificial intelligence to ensure safe and productive operations. Furthermore, it has led companies to an intelligent, autonomous supply chain, resulting in proactive and predictable maintenance.
. Additionally, it has also helped companies automate quality checks and innovate their products. [9] Financial services have witnessed a similar parallel transformation, with AI significantly enhancing efficiency in areas related to fraud and algorithmic decision-making. Nevertheless, research highlights that AI optimisation needs to be complemented by human judgement.

Though AI has shown significant potential in amplifying operational efficiency, its effectiveness remains rough across various ventures. Research suggests that AI adoption can lead companies to allocate more funds to financial investment, diverting focus from mainstream manufacturing intended by the company. Moreover, the benefits of AI are unevenly distributed, with large enterprises experiencing exponential gains, whereas smaller enterprises experience little improvement due to constraints.. Additionally, the implementation of AI requires consistent and timely investment and a strong managerial capacity, making it less accessible to firms of all sizes. Consequently, AI alone is insufficient to drive overall performance as a range of other factors influence its outcomes.

The recent expansion of AI has led to the emergence of hybrid operational models in which AI-driven optimisation is accompanied by human judgment. While AI enhances efficiency through automation and data-driven decision-making, its effectiveness remains dependent on human judgment. Human oversight remains essential, indicating that modern AI functions not as a replacement but as an expansion of human intelligence.[10]

While several studies emphasise the transformative potential of AI in enhancing operational efficiency, others argue that the impact of AI remains highly conditional even in today’s time. This depends on various factors like data quality, organisational capabilities and contextual complexity.

This paper attempts to analyse the impact of AI on the manufacturing and services sectors in an economy. This would be contrasted with human-centric approaches in the same sectors. Specific case studies in both these sectors will be examined, namely, JPMorgan Chase in the financial sector and Tesla in the manufacturing sector. Both would be examined with respect to the influence of both technology and human-centric impact on their revenue and profitability.

The methodology adopted would be of a mixed-method type, where both quantitative and qualitative analyses would be examined. The quantitative analysis would entail secondary data from authentic sources, which would be substantiated by qualitative analysis.

This paper analyses the importance of AI technology in the financial and manufacturing sectors, contrasting it with human-centric models that were primarily used earlier. How has this new technology impacted economic costs while using it? Looking at JPMorgan Chase and Tesla would help in understanding the impact of the adoption of AI in their work environment. What would the effects of such a technology have on the employment and productivity of the specific company?

2. METHODS AND MATERIALS

2.1 Research Design

A descriptive comparative secondary-data case study is employed in this study. The research examines the relationship between the increasing use of artificial intelligence (AI), automation, and other technologies and changes in operational practices, labour usage, productivity, efficiency, and cost. Tesla manufacturing operations and JPMorgan Chase financial services are selected as case studies because they represent two distinct operational settings: capital-intensive, technology-intensive manufacturing and knowledge-intensive, information-intensive financial services.

As there is insufficient experimental data from either company to measure the direct influence of AI on employment, productivity, or costs, only secondary data are used. The study involves comparative analysis of financial, personnel, technological investment, operational, and documented AI and automation information published by the companies.

2.2 Study Period and Data Sources

The key quantitative study period was 2010 to 2024, with earlier Tesla data used to provide context for the evolution of manufacturing automation.

Primary data sources included annual reports, related regulatory filings, investor relations materials, and official company documents issued by the respective corporations.

For Tesla, data on workforce, financial performance, manufacturing automation, robotics, artificial intelligence-powered manufacturing, computer vision, neural networks, demand forecasting, and other technologies related to manufacturing processes were considered.

For JPMorgan Chase, data on technology expenditure, workforce, efficiency ratio, revenue per employee, and documented applications of artificial intelligence in areas such as document processing, fraud detection, transaction monitoring, and large-language-model applications were considered.

Technology expenditure was treated as a measure of overall technological investment and was not treated as a direct measure of AI expenditure. AI adoption was considered separately through documented AI applications and reported AI use cases, while automation was considered through documented use of robotics and automated systems.

2.3 Source Selection and Inclusion Criteria

The sources selected for inclusion were assessed on the basis of authority, relevance, time period covered, and compatibility with the variables being examined. Annual company reports and regulatory reports were given priority for financial and workforce-related information, while official company documents were used for information relating to AI and automation.

Sources were included when they:

- were directly related to Tesla or JPMorgan Chase;
- provided information about AI, automation, employment, technology investment, efficiency, productivity, financial performance, or operational processes;
- related to a particular year or reporting period; and
- provided identifiable and credible information relevant to the study.

Sources that were duplicated, lacked a reporting period, or did not provide sufficient information relevant to the study were excluded.

In cases of conflicting values, the company's annual report or regulatory report was given priority for quantitative information. Different values based on different definitions were not combined.

2.4 Data Extraction and Preparation

The variables examined were:

Company	**Variable**	**Analytical purpose**
Tesla	Workforce employment	Examine changes in labour utilisation

Tesla	Automation indicators	Examine development of manufacturing automation
Tesla	Financial performance	Assess broader economic outcomes
JPMorgan Chase	Technology expenditure	Measure growth in technological investment
JPMorgan Chase	Workforce employment	Examine changes in labour utilisation
JPMorgan Chase	Efficiency ratio	Assess operating efficiency
JPMorgan Chase	Revenue per employee	Examine output relative to workforce

Where necessary, revenue per employee was calculated as:

Revenue per employee = Total revenue ÷ Number of employees

The data were standardised to comparable units before comparisons were made. Percentage measures were kept in percentage form while financial measures were interpreted based on each company's reporting convention.

Where data for a particular year were unavailable, the observation was treated as missing rather than estimated or replaced.

2.5 Comparative Analysis

The quantitative analysis involved longitudinal comparisons, percentage change, ratio, and trend analysis of the selected variables.

In the case of Tesla, workforce employment was studied alongside automation and financial performance. The analysis considered the distinction between relative labour intensity and absolute employment.

In JPMorgan Chase's case, technology expenditure was analysed alongside workforce employment, efficiency ratio, and revenue per employee. The efficiency ratio was used as an indicator of operating efficiency, while revenue per employee was used as an indicator of output relative to workforce.

The analysis examined whether periods of increased use of AI, automation, and technology were accompanied by changes in labour utilisation, productivity, and efficiency.

2.6 Qualitative Evidence

Qualitative evidence was examined descriptively using official company documents relating to the implementation and use of AI and automation.

For Tesla, the analysis focused on robotics, intelligent automation, computer vision, neural network applications, demand forecasting, and automated manufacturing systems.

For JPMorgan Chase, the analysis focused on applications including Contract Intelligence (COiN), AI-powered fraud detection, transaction monitoring, large-language-model applications, and other AI-powered financial processes.

The evidence was compared across years and between the two companies to identify recurring patterns and differences in the relationship between technology, labour, and operational processes.

2.7 Integration of Evidence

Quantitative and qualitative evidence were considered together during the comparative interpretation of the two cases. Quantitative results provided information on changes in labour, technological investment, efficiency, and productivity, while qualitative evidence provided context regarding the technologies and processes associated with these changes.

The study does not assume that increased use of AI or automation directly caused changes in employment, efficiency, productivity, or financial performance. Company outcomes may also be influenced by demand, economic conditions, production scale, restructuring, capital expenditure, acquisitions, and corporate strategy.

2.8 Limitations

The availability and reliability of historical data vary between Tesla and JPMorgan Chase. For Tesla, diversification through new manufacturing facilities, automobile models, and markets makes comparison of particular manufacturing processes difficult.

Neither company consistently reports AI expenditure as an independent financial category. Therefore, technology expenditure should be interpreted as an indicator of overall technological investment rather than direct AI expenditure.

Due to the use of secondary data, the study cannot establish causality between AI or automation and changes in employment, efficiency, productivity, or financial performance.

The historical automation indicators also vary in definition and reporting from year to year and are therefore treated as indicators of automation development rather than perfectly comparable annual measures.

Finally, the study examines only two companies and cannot be considered representative of all manufacturing or financial services companies.

3. RESULTS

3.1 Analysis of the Importance and Use of AI Technology at Tesla

Tesla's manufacturing operations incorporate automation and artificial intelligence (AI) across several areas, including manufacturing, vehicle safety, data analysis, and production processes. These technologies should be distinguished since automation and robotics are not necessarily AI-based. Tesla adopted a vision-based approach to self-driving technology using cameras around its vehicles. The company also implemented adaptive robotic automation involving machine learning and computational vision capabilities. In addition, Tesla implemented AI-based safety measures designed to improve the vehicle's ability to perceive its surroundings, monitor driver behaviour, and reduce the likelihood of crashes. These technologies include Vision Neural Networks, real-time analysis of different variables, and monitoring of behaviour.[11]

Tesla's operations also retain human involvement alongside automation. Machines perform repetitive tasks requiring precision, while human workers remain involved in designing, improving and supervising these technologies. Tesla also employs Production Assistants who receive on-the-job training and participate across different stages of production.[12] The available evidence therefore identifies both automated processes and continued human involvement within Tesla's manufacturing operations.

Tesla has also implemented intelligent automation systems in its operations. The company developed a demand forecasting algorithm using machine learning and real-time sales and customer reservation data to forecast future production requirements. These applications provide evidence of the use of machine learning and data-driven systems within Tesla's operations.

Table 1: Timeline of the Automation of Tesla's Manufacturing Operation

Year	Reasons for the division between automation and human-centric
2003	Tesla had no production at this stage, making AI optimisation irrelevant.
2008	Tesla started the Roadster’s production, implementing automation only in repetitive tasks

2012	Production of the Model S boosted production, so Tesla adopted more automation to boost efficiency
2018	Tesla pursued 'hyper automation' during Model 3 production, increasing the use of automated processes
2020	Tesla stabilised AI automation due to failures in 2018
2024	Tesla moved toward optimised automation, combining lessons learnt from the past by having AI only in the manufacturing process and humans for adaptability.

Sources: Adapted from the references listed in the manuscript [11 - 12]. This table lists some of the recorded advances in Tesla's manufacturing automation and related AI procedures during the years 2003 to 2024. "AI" stands for artificial intelligence. Automation and AI are considered two different areas and should not be taken as synonymous.

Table 1 presents the evolution of Tesla's use of manufacturing automation and related AI technology between 2003 and 2024. The facts indicate an increase in automation together with the continued presence of human input. Yet the timeline does not provide proof that the increase in automation or AI led to labor needs, efficiency, or profitability.

3.2 JPMorgan Chase

JPMorgan Chase provides evidence of AI adoption through applications involving document analysis, fraud detection, transaction monitoring, and algorithmic trading. One significant implementation was COiN, an AI-driven contract intelligence system. COiN extracts key clauses, including cancellation rights and obligations, converts unstructured data into structured information for databases and dashboards, and learns from previous documents and annotations.[13] The implementation of COiN saved 360,000 hours of manual work and reduced human error by 80%.[14]

JPMorgan Chase also used AI for fraud detection and transaction monitoring. Earlier fraud detection systems relied on rule-based processes that flagged transactions according to predetermined requirements. These processes could generate false positives and require manual investigation. JPMorgan Chase subsequently developed AI-driven fraud detection systems using machine learning to identify fraudulent patterns and reduce false positives. These systems were reported to be 3–4 times more efficient than older rule-based systems in detecting fraud.[15]

JPMorgan Chase has additionally expanded the use of algorithmic trading systems. Approximately 99% of the company's trading volume, particularly in equities, fixed income and foreign exchange, is executed algorithmically. Algorithmic execution is treated separately from AI adoption because algorithmic systems are not necessarily AI-based

Before the adoption of more advanced AI systems, several processes within the organisation relied substantially on manual labour. These included the review of loan agreements by lawyers and loan officers, a process estimated to consume more than 360,000 labour hours.[16] Fraud detection also required human analysts to investigate transactions identified by existing systems.

The adoption of AI-based systems occurred alongside changes in the company's broader technological expenditure. Technology expenditure increased from under $2B in 2010 to $10B in 2018 and $18B in 2023. However, technology expenditure represents broader technological investment and is not treated as a direct measure of AI expenditure The company's efficiency ratio decreased by 19% between 2010 and 2023.[16] Revenue per employee also increased from $621,727 to $878,290 in 2025.[17]

JPMorgan Chase's total assets exceeded $3.9 trillion in 2023.[15] The company also faced additional compliance requirements following the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, including stress-testing requirements and enhanced capital-ratio monitoring. These requirements increased compliance costs by $4 billion.[18]

The available evidence also identifies risks associated with AI-based systems, including software security, identity and authorisation, data governance and cyberattacks.[19] These risks create additional requirements for cybersecurity and data protection alongside the implementation of AI systems.

Overall, the results show that JPMorgan Chase has implemented AI-based systems across several operational functions, including contract analysis and fraud detection, alongside continued use of algorithmic systems. The available quantitative evidence also shows increases in technology expenditure and revenue per employee, together with a decrease in the reported efficiency ratio over the periods examined. These changes occurred alongside AI adoption; however, the evidence does not establish that AI caused these changes. Other factors, including company growth, acquisitions, regulatory changes, changes in product mix, geographic expansion, inflation, and broader macroeconomic conditions, may also have contributed.

4. DISCUSSION

4.1 Economic Impact of AI Adoption

The implementation of AI-based systems at Tesla and JPMorgan Chase indicates the increasing use of technology-driven operational processes. At Tesla, automation and AI-based systems are used alongside continued human involvement in manufacturing. At JPMorgan Chase, the implementation of COiN saved 360,000 hours of manual work and reduced human error by 80%, while AI-driven fraud detection systems reduced false positives and were reported to be 3–4 times more efficient than older rule-based systems.

These findings are consistent with potential efficiency gains from AI-supported processes. However, the precise economic impact of AI cannot be isolated with certainty, as the performance of both companies is influenced by several other operational and economic factors.

4.2 AI, Productivity and Operational Efficiency

Tesla implemented intelligent automation systems in processes including demand forecasting, using machine learning techniques based on real-time sales and customer reservation data. The company also applied adaptive robotic automation, Vision Neural Networks, and real-time analysis of different variables within its operations.

The timeline of Tesla's manufacturing operations shows a progression from automation of repetitive tasks in 2008 to increased automation during Model S production in 2012, the pursuit of “hyper automation” during Model 3 production in 2018, and optimised automation in 2024. Human involvement remained present through the design, improvement, and supervision of these technologies.

JPMorgan Chase similarly implemented AI-based systems in document processing and fraud detection, while algorithmic systems were used extensively in trading. These findings indicate that technology was associated with changes in operational processes in both companies, although the form of technological optimisation differed according to the operational environment.

4.3 AI and Employment

The impact of AI on employment presents a more complex outcome than direct replacement of labour. Employment increased at Tesla, from 10,161 employees in 2014 to 125,665 in 2024, and JPMorgan Chase, from 255,698 in 2012 to 317,233 in 2024.

At Tesla, increasing automation did not remove human involvement from manufacturing. Humans remained involved in adapting to changes, designing, improving and supervising technologies. Tesla also recruits Production Assistants who receive on-the-job training and participate across various production stages.

JPMorgan Chase similarly moved from manual processes towards greater use of AI and algorithmic systems, while human traders, lawyers, loan officers and analysts continued to perform important roles. The increase in workforce employment alongside increasing AI adoption therefore indicates that AI adoption does not necessarily result in an immediate overall reduction in employment. This is consistent with empirical research showing that automation can increase productivity while having mixed effects on employment, as new tasks may offset labour displacement.[20]

4.4 Comparative Analysis of Tesla and JPMorgan Chase

Tesla and JPMorgan Chase demonstrate different forms of technology-driven operational transformation. Tesla applies AI and automation primarily within manufacturing, demand forecasting and vehicle-related systems, whereas JPMorgan Chase applies AI to document processing, fraud detection and transaction-related processes.

The comparison indicates that the effects of technological optimisation differ according to the operational environment. At Tesla, technology is more closely connected with physical production and automation, while at JPMorgan Chase it is more closely connected with information processing and financial services. In both cases, human involvement remains present alongside technological systems.

However, these companies are not directly comparable because they operate in different sectors, have different business models and differ substantially in scale. Therefore, the comparison is used to identify differences in the application of AI rather than to determine which company experienced a greater effect from AI adoption.

4.5 Limitations and Alternative Explanations

The main limitation of the analysis is the lack of authentic and continuous data for Tesla. Tesla expanded into the manufacturing of newer models and different parts of the world, leading to gaps in data for individual models over a continuous period of time. The research would also have been more meaningful if a larger number of companies had been considered, but this was not possible due to the paucity of time and finances.

The analysis relies on selectively available public data, including corporate and media sources. Changes in accounting definitions across years may also affect comparisons. Furthermore, technology expenditure is broader than AI expenditure, and algorithmic execution is not necessarily equivalent to AI adoption.

Isolating the impact of AI from the numerous factors determining financial performance remains a challenge. The increase in revenue, profitability, workforce employment, and technology expenditure cannot be attributed entirely to AI technology. Company growth, acquisitions, regulatory changes, product mix, geographic expansion, inflation, and broader macroeconomic conditions may also have contributed. The absence of a counterfactual showing how either company would have performed without AI adoption further limits the ability to establish a causal relationship.

The analysis also demonstrates that AI implementation has its own economic costs. Greater AI-optimised systems are prone to cyberattacks, which can corrupt data and require further economic costs to develop cybersecurity. Therefore, the economic impact of AI should be considered in terms of both potential efficiency gains and the costs associated with implementing and maintaining AI-based systems.

5. CONCLUSION

Given the extensive use of AI technology in the world today, Tesla started using capital-intensive AI-based systems right from the beginning of its operations. The use of labour in their factory was limited, and over time, as they expanded their operations, the extent of capital-intensive AI-based technology increased.
JPMorgan Chase, on the other hand, increasingly incorporated AI and other technology-based systems into its operations as these technologies became more specialised in the financial and fintech sectors.This has continuously been on the rise as AI technology has become specialised in the financial and fintech sectors.

With the continued development of AI, some tasks may require less direct human involvement; however, the overall effect on employment cannot be determined from the present analysis. The only option then for the labour force is to continuously skill themselves so that they become indispensable to companies, resulting in employment instead of replacement.

The results can be restricted because of the availability and comparability of the public data, difference in the size and sectors of the two firms, and lack of a counterfactual that would help to identify the influence of the AI alone. Further research can involve the analysis of more firms in the manufacturing and financial services sector based on longitudinal data. The author declares no conflicts of interest related to this work

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