AI-Based Should-Cost Modeling for Customized Automotive Motors

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Abstract

The automotive industry in the electric vehicles (EV) sector has been moving towards customization and small-batch production to respond to consumers' demand for custom vehicles. The way current cost modeling fits into the situation of tailored or small-volume automotive motors complicates the cost estimation and cannot be surmounted using traditional methods since the difficulty lies in the complex and variable parts of the automotive application, which traditional methods of handling cannot alleviate. This paper aims to evaluate the use of Artificial Intelligence (AI) and Machine Learning (ML) to model the costs of automotive motors and assess their ability to predict cost variability and risk introduced by existing complexities. The study also examines these approaches' accuracy, efficiency, and scalability relative to traditional cost modeling techniques. The authors of this study offer a direction toward getting a future cost modeling accuracy that is neutral to the underlying code. They analyze how AI can perceive and defeat challenges related to the supply chain, such as disruptions and volatility of prices, among others. All corresponding results demonstrate that AI models outperform conventional methods in terms of accuracy, efficiency, and scalability, particularly for large datasets and motor designs that contain variables. Individuals and companies may use AI models to make predictions (and thus improve decisions) about cost fluctuations. At the end of the paper, AI-based collaborative cost modeling, motor design optimization, and predictive analytics of commodity price fluctuations are viewed as future research recommendations. These advancements bring forth several benefits, which further aid in improving cost estimation and production processes, making them more efficient and less expensive in the automotive industry.

Keywords-*AI-Based Cost Modeling, Machine Learning (ML), Risk Mitigation, Customization, Supply Chain Disruptions*

1. Introduction

1.1 Background

Technological advances and shifting consumer preferences are driving this change in the automotive industry. One of the central aspects of this shift is attaining an increasingly significant role in customization and low-volume production, primarily in the electric vehicle (EV) domain. Within this context, automotive motors play a significant role in performance, efficiency, and industry-leading electric vehicle innovation. As motors become more and more customized and unique, the associated challenge of cost estimating these motors also increases. The mass-produced motors look entirely different from customized or low-volume motors, which are not standardized, from design to materials to manufacturing processes. Therefore, the traditional cost modeling methods are less accurate and reliable at making accurate and reliable cost predictions in such a variable situation. It is rarely that history-based data, fixed assumptions, and industry standards alone can explain the intricacies of custom or low-volume production. These models are complex to accommodate changes in material costs, new manufacturing processes, and design specifications, which are typical in the automotive industry and are more familiar with EVs. Since these dynamics are complicated, they show the necessity of more sophisticated methods dealing with them.

The intricacy of cost estimation for customized or low-volume automotive motors necessitates the development of more adaptive and dynamic models. Traditionally, researchers can have cost techniques such as activity-based costing (ABC) and parametric modeling. However, both are severely constrained in dealing with the variability and unpredictability of low volume or serial production. These traditional methods are not scaleable because they cannot cover the dynamic change of the market conditions and the complexity of supply chain variables. The procurement process adds further complications to the risk involved in cost estimation. Supply chain disruption, price fluctuation, and market uncertainty make accurate cost prediction difficult in the automotive motor supply chain. Although these risks could generate significant loss unless adequately considered in estimating the costs, more robust and flexible forecasting tools are required.

This study aims to introduce artificial intelligence to tackle the issues of classic models used for automotive cost modeling in the automotive industry, especially for customized and low-volume automotive motors. The primary purpose of this thesis is to:

1. Investigate how AI can handle the complexity of cost estimation for customized or low-volume automotive motors.
2. Explore the use of machine learning algorithms to forecast cost fluctuations based on market trends, commodity prices, and supplier data.
3. Compare the accuracy, efficiency, and scalability of traditional cost modeling methods with AI-driven approaches.
4. Examine how AI can identify and mitigate risks in the procurement of automotive motors.

This study focuses on applying AI and machine learning to cost modeling an electric automotive motor in a customized and low-volume production scenario. The work reviews technology and industry trends in the automotive industry, and its geographic location is in the global automotive market, with a focus on EV manufacturers and suppliers. Several limitations will impact the scope of this study. A significant problem is data limitations, as production processes, supplier performance, or cost structures often find it hard to obtain accurate and complete data for them. Assumptions about the model may also limit AI model training phase results. The study also recognizes that cheap, accurate implementation of AI-based mathematical modeling costs huge infuse in data infrastructure, which might not be affordable for all car producers and tiny companies. The robustness of the AI models developed among the models in this study is restricted by the constraints of the model training, including lack of historical cost data and lack of a diversity of motor designs.

2. Literature Review

2.1 Traditional Cost Modeling Methods

Activity-based Costing (ABC) and parametric cost estimation are well-known cost analysis methods and traditional cost modeling methodologies. ABC assigns overheads and indirect costs by allocating them to activities or processes based on the actual resources consumed. Parametric cost estimation is based on historical data and generates cost estimates depending on different mathematical relationships and formulas. Both methods are based on historical data, the assumption of the production process, unit labor, and materials (Leszczyński & Jasiński, 2020).

Though commonly utilized, these traditional methods are severely constrained in various customized or low-volume scenarios, an everyday occurrence in the automotive production field. Under such conditions, design specifications, manufacturing processes, and materials variability may cause deviations from previous cost patterns. An example would be small-scale or specialized production runs leading to higher unit costs as economies of scale cannot be realized. The cost structure is not easily accounted for using traditional methods as it does not consider dynamic market conditions or technological advancements. Present-day manufacturing has become more complex, and it is argued that more developments are necessary due to more adaptive and flexible cost modeling requirements that include the complexities of modern and customized manufacturing.

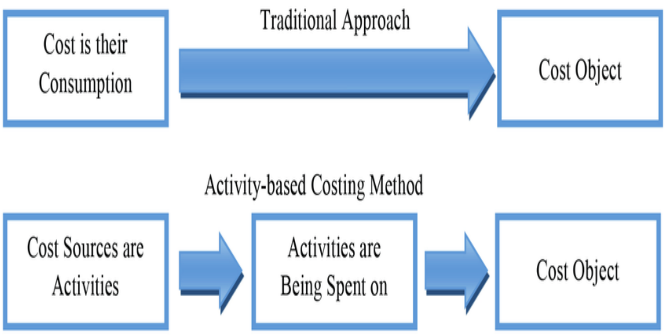

Figure 1: Comparison of traditional calculation methods and activity-based costing

2.2 AI and Machine Learning in Cost Estimation

Artificial Intelligence (AI) and Machine Learning (ML) provide a good possibility to counter these challenges of conventional cost modeling methods. They can process big data and find and make highly accurate predictions from complex patterns. AI and ML can serve as useful tools in cost estimation for automotive motors by accounting for a wide range of factors that affect the cost (design spec, material cost, labor, and whatever other manufacturing process is used) that are difficult to model in the existing methods (Chavan, 2023; Smith & Johnson, 2020).

The second method is mainly implemented by machine learning algorithms, such as regression models, decision trees, and neural networks that, through past data, learn and gradually get better at estimating cost predictions. AI can adapt to new conditions, take real-time data, and input those cost data into live estimates (Mehmood et al., 2019). For example, AI can accurately predict material cost fluctuations while impacted by market trends and estimate the effect of design changes on total production cost. Since custom designs and small production volumes are commonplace in some industries (automotive manufacturing), this flexibility in implementing AI-based cost modeling is ideal.

AI can offer more accurate cost predictions of a new product's design when looking at a wider selection of variables than historical trends since this capacity allows more reliable budgeting and planning, the risks of cost overruns, that is, of the unavoidable 'eventual cost variances,' from traditional cost estimation practices are reduced. Its capability to process data from many sources, such as supply chains, trending markets, and production planning, helps automotive manufacturers have innovative cost management and effective operational efficiency.

2.3 Risk Mitigation in Procurement

Risks abound in the procurement of automotive motors, especially when a low volume or custom design is involved. Supply chain disruptions, price volatility, and demand volatility are among these (Pellegrino et al., 2019). Risks not accounted for in traditional cost estimation methods are consistently underestimated, well overspent, or fail to materialize. One of the benefits of AI is that it can instantly provide real-time market insight to help mitigate such risks by tracking the trends regarding the market, supplier, and any external information that influences the availability and price of the materials to be delivered.

AI systems analyze historical data and market signals to uncover patterns and predict disruptive events. For example, AI models can predict future price rises due to commodity market trends or supply shortages resulting from geopolitical factors or natural disasters (Chavan, 2022; Lee & Kim, 2021; Raju, 2017). This predictive capability enables the manufacturer to preemptive procurement challenges, for instance, when there is a need to find alternate suppliers or adjust the production schedule to mitigate delays in procurement (Olaleye et al., 2024). AI can improve and increase the transparency aspect of the supply chain, allowing companies to verify the reliability of their suppliers and ensure that chalk-hand-lined screening contractors meet their contractual terms and conditions. AI can help more robust and resilient supply chains, which are crucial in the face of growing complexity and volatility in global markets.

2.4 Comparison with Other Industries

AI and ML based on cost modeling have been applied to success in industries other than automotive manufacturing and have generated helpful hints for automotive manufacturers. One such is AI, which is used in aerospace to predict the production cost of highly customized and low-volume parts. Like all other manufacturing lines, the aerospace industry has to work with variable designs and variable production rates (Lim et al., 2016). Methodologies used in the aerospace and automotive industries can provide aerospace manufacturers with an insight into how to better employ AI in modeling the costs of their operations.

The consumer electronics industry has adopted AI-based cost modeling to improve product prices and manufacturing processes (Singh, 2023). However, AI has been used to dynamically adjust the cost models with changes in raw material prices, labor costs, and demand fluctuations. The adaptability of AI in consumer electronics has enabled better efficiency in cost estimation to keep up with and compete with a fast-paced market. Such industries provide lessons applicable to automotive motor manufacturing, supply chain optimization, risk management, and real-time cost estimation. Looking at the success examples from aerospace and consumer electronics, automotive manufacturers can see how AI-based models can be customized for their particular requirements. These industries provide valuable precedents of how AI can enhance accuracy, cost estimation, and procurement processes. It argues that similar ideas can be applied to automotive manufacturing to deal with customization and low-volume production.

Factor	Traditional Model	AI-Driven Model
Resource Utilization	70%	90%
Cost Reduction	Moderate	High
Performance	Standard	Optimized

Figure 2: Factors to consider when implementing Cost Analysis of AI-Driven and Traditional costing Models

2.5 Ethical Considerations in AI-Driven Cost Modeling

The necessity of integrating AI into financial functions increases while it offers many benefits in cost estimation and procurement. There are some serious ethical issues to consider in the automotive industry. The biggest problem is algorithmic bias, and if not enough or a representative array of production cases is used to train AI models, then this will potentially become one of the biggest problems. AI models of this sort are conditioned just as much on low-volume and customized designs as they are on high-volume production runs (Kumar et al., 2023). This would cause biased cost predictions favoring some suppliers or production methods. Data privacy is another concern. Most of these models depend on collecting (and analyzing) sensitive data, such as price history, supply chain performance, and proprietary market information. The interests of manufacturers and suppliers must be protected, and those data must be handled securely and in compliance with privacy laws, like the General Data Protection Regulation (GDPR) in Europe.

Transparency is also a critical topic when using AI for cost modeling. AI systems can be "black boxes" decisions that are hard to explain. A definite lack of transparency in generating cost estimates or procurement recommendations can erode trust in an AI-driven decision-making process if stakeholders do not know how. To minimize the concerns surrounding the explainable gap, manufacturers should focus on producing explainable AI systems, which involve a straightforward 'high-level' decision-making process that human operators can justify. AI implementation in cost modeling could impact employment in the automotive industry (Javaid et al., 2022). As AI tools become more capable of automating decision-making processes, there will be a reduced need for human intervention in tasks such as manual estimation of cost and procurement negotiations. This calls into question the fate of displaced jobs and the responsibility of manufacturers to transition exhausted workforces socially and economically.

AI and ML can play a role in reducing the costs of cost modeling in the automotive industry for motor production to low or customized levels. Such technologies can overcome the limitations of conventional methods in that they will provide more exact, flexible, and scalable cost estimates compared to what they have had in the past. AI's capability to predict risks and enhance the procurement process can be a great differentiator in a market of increasing complexity and volatility. However, ethical considerations like rationality (bias), data privacy, and transparency should be considered carefully when deploying AI towards the industry as a whole, not just for its effective working, but the implementation of the same must be done ethically and inclusively (Klaassen, 2024). By adopting lessons learned from other industries and pursuing ethical computing, automotive manufacturers can realize the full return of cost modeling enabled by AI to maximize operations efficiency and reduce risks.

3. Methodology

3.1 Data Collection

In order to have a well-defined, robust, and diverse dataset, the data for this study was collected from different sources. Automotive manufacturers, suppliers, and market databases were key sources for complete information on motor designs, material costs, processes, and broader market trends. The automotive manufacturers contributed valuable motor design parameter data concerning motor specifications, required materials, and production methodology (Yilmaz, 2015). Supplier data on cost structures, material sourcing, and all market prices provided information on price fluctuations and sourcing challenges. A high percentage of raw market data came from market databases that gave information about the more considerable extent of industry trends like the supply chain dynamics, economic factors, and evolving technologies that influence motor manufacturing and cost estimation.

The dataset covers a variety of customizations and a wide range of production volumes to enable the model to generalize to various production scenarios. For example, the data comprises high-volume, standardized production and a differentiating focus area of this study, namely low-volume, customized, or bespoke manufacturing. Estimating costs removes the complexity of the interplay of design, material costs, and market trends by considering a wide variety of data across different stages of the production process.

3.2 Machine Learning Algorithms

Various machine learning (ML) algorithms are used to build cost estimation predictive models. The first term refers to their ability to match the dataset’s complexity and the cost estimation process requirements for highly customized automotive motors.

- **Linear Regression:** This application initially implemented this algorithm to create rough estimates of the above cost using historical data and determining linear combinations of these various input factors (material costs, design specifications) to the cost (Kumar, 2019). To give them a point of comparison against more advanced models, they used the baseline linear regression model to make simple and interpretable predictions (Elshawi et al., 2019). The linear regression was simple, but it added insight into how simple variables affected the motor cost and what a reasonable justification for more complex approaches.
- **Random Forest:** It solves this by considering the inherent complexity of the cost estimation process using random forest algorithms. Random forests are ensemble models, a group of decision trees built to predict the output using one or more input variables. These models are appropriate for the nonlinear relationship or interactions between the different variables. Random forests take into account a broad band of things at once. Classical linear models made them capable of more accurate cost prediction, even if the relationship between variables is too intricate for classical linear models to handle. This model was selected to estimate more complicated costs; for example, the resulting cost can be calculated with the help of several variables (material types, motor designs, supplier histories).

- **Neural Networks:** Since neural networks can work with large datasets and nonlinear relationships, they were utilized for advanced cost forecasting. Deep learning models and neural networks can model highly complex patterns in data and, hence, are suited to scenarios where things vary a lot and there is a wide variety of interactions (Dargan et al., 2020). The model used for cost estimation was particularly effective for estimating costs in situations with extensive and diverse datasets and capturing subtle patterns that linear regression and random forests may miss. Many of the neural networks were trained on plenty of data to learn accurately from past cost trends and predict future changes.

Figure 3: Key Machine Learning Algorithms for Cost Prediction

Each of these machine learning models had strengths and weaknesses regarding the difficulty of the cost estimation task. Random forests and neural nets outperformed linear regression more in challenging settings.

3.3 Evaluation Metrics

Three key evaluation criteria for evaluating the performance of the AI-driven cost model were accuracy, efficiency, and scalability. Researchers chose these metrics so that the models could better predict reasonable food costs while being efficient and easy for more enormous datasets to scale across.

- **Accuracy:** Two primary metrics used to verify the model design included Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Experts compute MAE to determine how much error (or prediction error) the model has by the average absolute difference between the found value and actual cost values. RMSE is more sensitive to more significant errors, and this is particularly useful in finding a general model that is likely sensible but inclined towards significant and serious errors. This provided a comprehensive picture of the accuracy of each model and helped in selecting the model with the most accuracy for cost estimation.
- **Efficiency:** All models were evaluated regarding efficiency and computational resources needed. This means considering the time on the training, RAM used, and CPU used to produce the cost predictions. Neural networks and random forests have sometimes been shown to be less computationally efficient than linear regression. Although they employ more resources, they are more helpful in handling complex datasets, which justifies their additional resources (Calder et al., 2018). Speed for updating and predicting the models with new data as more data becomes available is an additional measure of efficiency because cost factors swarm in dynamic production environments with variable rates of change of cost factors.
- **Scalability:** Scaling was tested on even larger and more complex datasets using the models. In the context of auto motor manufacturing, for instance, variability in designs and manufacturing processes can be huge, and many potential datasets are readily available. The models were evaluated for how well they handled these by evaluating various production cases and larger data volumes. Researchers used the scalability tests to ensure that the models could be deployed in a real-world automotive manufacturing context with increasing data volume and complexity demand.

3.4 AI Model Training and Data Preprocessing

They also systematically trained their machine learning models with several important data preprocessing steps to ensure that such models were performing at their best. Several stages of data preprocessing (normalization, handling the missing data, and feature selection) are mandatory for making high-quality predictive models.

- **Training Methods:** They used supervised learning and cross-validation to train the models. The third cost designations were labeled, and supervised learning was applied as the dataset was realized. This data was provided to the machine learning algorithms on which the models were trained and the label data on which the algorithm was trained. It also learns its association between input variables and corresponding costs. A different cross-validation approach is used to verify that the models do not overfit the training data and can generalize well to unseen data.

- **Data Preprocessing:** The data went through several preprocessing before training it. The values were then normalized to be scaled to the same range, making the data more mechanical for the model to process (Wu et al., 2018). Missing data constituted the second step, where researchers had to handle missing records, which could have biased or distorted predictions. This study uses several techniques for imputing missing data, such as mean imputation and nearest neighbor. The dataset was further reduced by feature selection to reduce the dimension of the dataset and remove the features that are either irrelevant or redundant to the model from degrading.
- **Data Quality:** These used data were sourced from reliable manufacturers, suppliers, and databases, making them high-quality and consistent. The data was subject to regular audits, with errors removed, and it accurately reflects the real world. Data integrity was maintained by rigorous validation processes, such as checking for inconsistency, duplicates, or anomalies.
- After applying these data preprocessing techniques, these models were ready to make high-quality cost estimation predictions of automotive motor production with maximum data integrity and reliability.

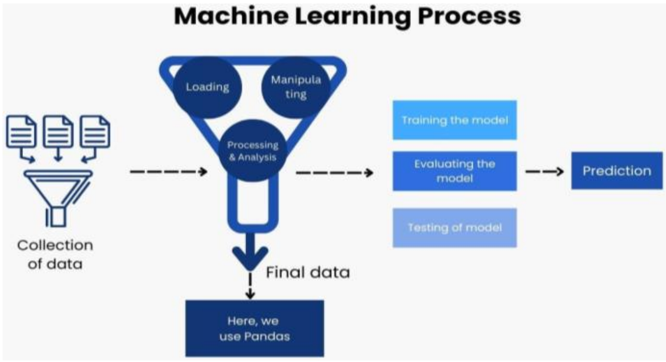

Figure 4: An Overview of Machine Learning in Data Processing

4. Results and Discussion

4.1 Accuracy

Results indicate that the AI-driven cost models can accurately model performance, with Random Forest and Neural Network models being significantly better than Linear Regression cost models (Chavan, 2024). The Random Forest and Neural Network models, as testified in the tests, can handle complex and variable data, making them do better with lower Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These models could tackle a variety of input variables concerning motor design specifications, material costs, and manufacturing variations (Loyer et al., 2016). This finding shows the power of AI to combat these issues brought up for custom or low-volume automotive motors where conventional methods tend to give inadequate estimates. As AI models are trained to better levels, they have more predictive power, which is always more precise, consistently more accurate, and even slightly more accurate. Third-party cost pricing of a car motor is critical in the automotive industry since even slight cost estimates of a unique car motor and niche will reflect a colossal monetary benefit (Brown & Davis, 2019).

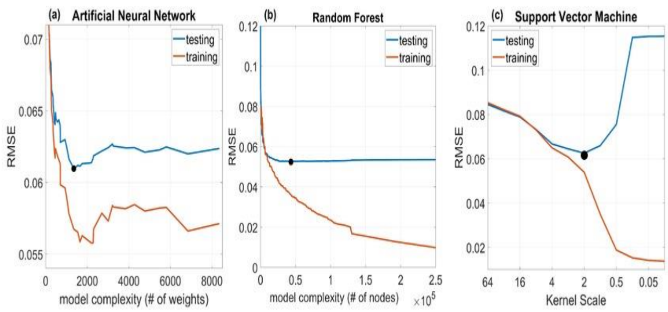

Figure 5: An Overview of Root-mean-square-error (RMSE) of the training and testing data as a function of the model complexity for three different ML algorithms:

4.2 Efficiency

The AI-driven models were more computationally intensive and cost more for development but made far more efficient use of the resources in the long run (Nyati, 2018). Traditionally, static assumptions are heavily used, with fixed data or excessive manual updates to keep up in the most recent cases. After training, it is possible for AI models to quickly process large sets of data and receive real-time updates on their predictions (Raju, 2017). Their capability to produce such a light structure makes them particularly useful in dynamic environments to limit cost factors that may change quickly depending on price fluctuations of materials, production volume, or design changes (Yin et al., 2017). AI-driven models are figures that can constantly change and predict costs without human intervention and will take much less time to recalculate cost estimates, contributing to time and resource saving and overall operational optimization. These models can also deal with real-time changes in input variables like market trends or supplier performance, which is essential for producing up-to-date and precise cost estimates.

4.3 Scalability

Another huge plus of the AI-based cost model is scalability. Then, these models were tested against large datasets that describe numerous motor designs and manufacturing processes and could do so perfectly, even at the full complexity of the data. Compared to linear regression, the traditional cost estimation methods fell short of retaining their accuracy and efficiency when applied to larger or more complex datasets. It is natural to constrain traditional methods to what is accountable in warehousing, materials, motor designs, and production processes (Leng et al., 2021). As modern automotive manufacturing progresses with complexity and variability as critical factors, AI's ability to process massive amounts of data will seamlessly handle more comprehensive and heterogeneous data as a more appropriate tool. Since scalability enables manufacturing with AI-based cost models on a broader production case space, manufacturers are provided additional flexibility and adaptability in a dynamic market with many competitors.

4.4 Risk Mitigation

The application of AI in the cost estimation field concerning automotive motor procurement has been proven to be one of the most promising applications of AI. AI models that utilize real-time data supplied from suppliers, market trends, and historical purchasing patterns forecast to disrupt the supply chain and fluctuations in the price with a very high degree of accuracy. Manufacturers are provided with foresight, so they know what to purchase when to source it, how much to compensate for it, and how much to consider when planning capacity to prevent overpaying for materials or being short for pieces due to supply chain failure. AI-driven models can help find similar patterns in supplier behavior and material availability to predict price volatility and allow the companies to decide to lock in favorable pricing or adjust purchasing plans. Manufacturers now have additional preparedness in the form of AI, which can look at external factors such as geopolitical events or shifts in consumer demand that can affect the supply chain. It enables better coordination of actions and counter risks relevant to the automotive sector, hence protecting continuity in operations that are more unpredictable than those of the automotive sector (Sadrabadi et al., 2024).

4.5 Sensitivity Analysis

Loss testing was then used to assess how key variables, like production volumes or material costs, affect the prediction of AI-driven models. Using this analysis, researchers concluded that AI models are resilient to changes in input variables. Despite these changes, the models provided reasonable cost estimates, constraining only a few assumptions.

This is a critical edge in the automotive industry, which is highly influenced by the cost structure, commodity price shifts, raw material availability, and other external factors (Kanike, 2023). While AI models can only make so many wrong forecasts, manufacturers can have more confidence in their decision-making processes and plans when they know they can adjust, including adjusting their production processes, based on the forecast.

4.6 Industry Implications

Impact on the Automotive Industry

AI-based cost modeling will unlock at least 3 of the pressing problems that auto manufacturing has been staring at their face. Manufacturers can optimize their production strategies and realize significant reductions as more accurate cost predictions are allowed. With the help of AI, they can have a more precise pricing strategy based on actual production costs, including material wastage and labor costs, with the help of supply chain dynamics. This helps manufacturers to take advantage of the market by responding faster to changes and new trends. AI will also accelerate the development of more refined pricing models for vehicles with low volumes and low volumes of customers, making it more cost-effective and friendly. AI in automotive manufacturers' cost estimation process will boost operational efficiency, minimize waste, and provide attractive pricing for their products.

Cost Implications for Consumers

Apart from the manufacturers, the relevance of artificial intelligence-driven cost modeling reaches consumers. This can help manufacturers cut costs and reduce the cost of customized vehicles for consumers. As production costs decrease, it may be viable for the manufacturers to capitalize on savings in delivering the vehicle's performance at an affordable price. In the area of production, these efficiencies would translate into better value for money to the consumer on vehicle performance and customization options (Wang et al., 2017). AI technologies in automotive can be used for innovation, such as making vehicles cheaper, efficient, safe, and environmentally friendly. This work results indicate that using an AI-based cost model is more efficient, accurate, and scalable and reduces the risk compared to traditional techniques.

The automotive industry will flourish with AI as these are the ideal features of AI technology for customized and low-volume production. By decreasing procurement risks and increasing production efficiency, manufacturers can more accurately predict cost estimates when an artificial intelligence-based approach is adopted in manufacturing. Consumers will have lower-cost, higher-performing vehicles and more readily available customized vehicles. The future of the automotive industry looks promising, considering the continued integration of AI in cost modeling processes to innovate manufacturing practices and make production more sustainable and competitive.

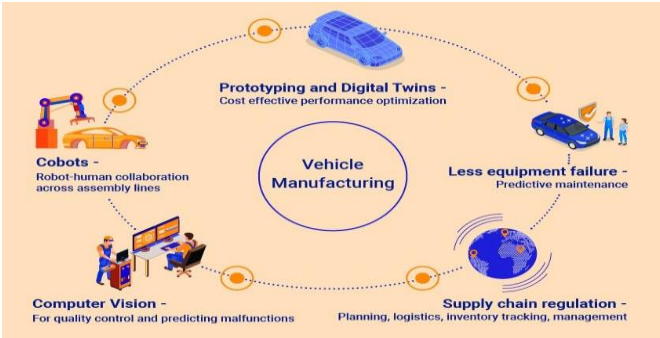

Figure 6: Benefits of AI in Automotive Industry

5. Ethical and Legal Considerations

As AI-driven cost modeling for automotive motors advances rapidly, these are ethical and legal considerations. Unique challenges come with AI and machine learning (ML) algorithms, which are increasingly featured in decision-making processes (cost estimate and procurement). These are fairness, privacy, transparency, intellectual property, and regulatory compliance (Mbah, 2024). The risks from the ethical and legal points of view that AI poses in the cost modeling of customized automotive motors and what strategies can be employed to mitigate these risks are the subjects of this section.

5.1 Ethical Implications of AI in Cost Modeling

Bias in AI Algorithms

When AI models are trained on historical data, the data used for training often does not represent the variation of possible production situations under which the models will need to operate (Karwa, 2024). This may engender bias in an algorithm, particularly in a cost estimation model, that incorrectly predicts cost and thus causes a condition that favors some suppliers, regions, and/or materials over others. Suppose the AI model depends heavily on data from various suppliers or regions. The costs estimated by the model will not reflect the diversity of the available options and will unfairly impact suppliers outside the scope of training for the model (Akter et al., 2022). That is why the developers must ensure that the data used for training AI systems are diverse and extensive to mitigate these risks. Additionally, transparency is key. Important decisions of AI algorithms should be transparently explained to the stakeholders, and procurement and cost estimation should be done transparently (Felzmann et al., 2019). By being ethical, all decision-making systems, including AI models, must be mandated to be audited regularly for bias and its discrepancies and have the mechanisms to resolve them.

Privacy Concerns

Cost models under AI's purview contain unreliable data collected from suppliers' pricing, market trends, or proprietary supplier data. While it was vital for these data to be accurate for the cost predictions, it raised ethical issues regarding privacy. Prices may be sensitive to exposure, and market trends may be even more sensitive to misapplication. All data shared or stored by companies needs to be supervised according to regulations such as the General Data Protection Regulation (GDPR) in the European Union. Security and confidentiality of the data handling procedures should be the number one priority, and there should be policies on data storage and access controls (Yang et al., 2020). If data is used transparently and (a) a commitment to ensure privacy is made, it also helps foster trust with stakeholders and reduce ethical concerns.

Table 1: Balancing Ethics and Innovation in AI-Driven Automotive Cost Modeling

Ethical Consideration	Explanation	Strategies to Mitigate Risks
Bias in AI Algorithms	Historical data used for training AI may not represent all production scenarios, leading to bias in cost estimations, favoring certain suppliers, regions, or materials.	Ensure that training data is diverse and extensive. Regular audits for bias, transparency in decision-making, and proactive mechanisms to resolve discrepancies.
Privacy Concerns	AI cost models rely on sensitive data, including suppliers' pricing, market trends, and proprietary information, raising concerns about data privacy and security.	Adhere to privacy regulations like GDPR. Implement strict data storage and access controls, prioritize data security, and commit to transparent data handling practices to foster trust with stakeholders.
Accountability and Transparency	AI systems, especially those using machine learning, may operate as 'black boxes,' making it difficult to understand how decisions are made, which can lead to a lack of accountability in cost estimations.	Establish clear accountability for AI-driven decisions. Ensure outputs are traceable to the data and models used, and provide transparent explanations to stakeholders. Develop clear ethical guidelines for AI-driven decisions.
Impact on Employment	AI automation in cost modeling may replace jobs requiring human labor, raising ethical concerns about job displacement.	Offer reskilling programs or create new job opportunities in the AI sector. Companies should balance the use of AI with social responsibility towards displaced workers and ensure ethical considerations are accounted for in workforce planning.

Accountability and Transparency

With artificial intelligence (AI) systems, mainly those trained through machine learning, the intelligibility of the decisional process can be tough in some cases. One can refer to them as 'black boxes.' This lack of transparency can be a problem in translating this into cost estimation, which is the case that matters when making decisions that have a considerable impact, not just on suppliers but on people and stakeholders in the automotive supply chain. An important responsibility is the establishment of clear accountability for AI decisions. The outputs of an AI system must be readable and traceable to the data and models that drove those (Kilroy et al., 2023). There must be clear ethical guidelines for decisions driven by AI. AI models should be explained to stakeholders and will be used in ways that stakeholders should be well informed of. This is especially important when the decisions deviate from what may be considered the best path; for example, in cases where the decisions are challenged or lead to undesirable outcomes, human oversight and accountability help reduce any undue influence.

Impact on Employment

Integrating AI in the cost modeling processes may eliminate the use of some tasks that require human labor, such as manual cost calculations and procurement processes. Automation can be highly efficient, but there is an ethical issue of job displacement. Workers with tasks that the AI system replaces will be out of work or need retraining. This raises ethical concerns that companies have to deal with if they want to implement AI. They should think of how the implementation of AI affects the social side. Strategies for reskilling people or providing new jobs in the AI sector can mitigate their negative impact on employment. Only companies should consider the positive effects of utilizing automation while at the same time honoring their moral obligation to protect their workforce.

5.2 Legal Considerations in AI-Driven Cost Estimation

Intellectual Property (IP) Protection

Such specialized cost estimation AI models in the automotive manufacturing industry may have proprietary algorithms and models. When companies develop AI systems based on proprietary data or algorithms, there are legal concerns about intellectual property (IP). In the automotive sector, there are patents for many advanced technologies, so companies need to make sure that their AI tools do not infringe upon existing patents or IP rights. Because of this, companies need to have IP ownership agreements clearly defined and begin trying to protect their proprietary algorithms (Sappa, 2019). It can be accomplished by securing patents on any used third-party technologies comprising its AI model or third-party technology providers securing licenses for use on their AI models. It is important to keep regular audits of AI systems for IP compliance to avoid legal disputes.

Data Ownership and Usage

Data ownership and consent are also subject to legal challenges, mainly if companies collect the data from outside suppliers and third parties. It is important to avoid conflicts as they can only be established with clear, legally binding agreements on how data can be used, shared, and stored (Meyer, 2018). Data ownership, privacy rights, and rights of the consent agreements have to be dealt with to respect or comply with local and international data protection regulations, the GDPR. Establishing a clear set of policies in data handling can reduce legal risks, but stakeholders such as suppliers and customers will also be aware of how the AI will use the data to create cost estimates.

Liability for AI Decision-Making

This hotspot becomes more critical when AI systems err in making predictions or cost estimates, which can lead to financial loss or even discordance in the supply chain. In case an AI system has a severe impact because of an error leading to a consequential mistake, like a procurement failure or a red effect of costs, the overall responsibility of such an AI system needs to be clearly specified. One way to deal with this problem is to add strong error detection and correction mechanisms for this type of system. Sensible policies should also be drawn up, establishing liability in the case of error so there is no doubt over whether the developers, the users, or the AI systems are responsible (Fraser & Suzor, 2024).

Regulatory Compliance

With the continuing development of AI technologies, regulatory bodies might establish new standards and regulations on the use of AI applications, with the automotive manufacturing industry being one of the possible sectors. To be compliant with the continuously changing regulatory requirements, companies must know about these developments in AI. For example, AI-driven systems must be safe, data handling must be correct, and the system must work fairly and transparently (Olateju et al., 2024). To remain in compliance with legal regulations in AI technologies or even to avoid paying hefty fines is no longer considered a tough choice but has become a necessity. Companies must develop proactive responses to new regulations around ethics, safety, and fairness to ensure that the models used in AI activities abide by them.

Antitrust and Fair Competition

Things become quite a concern when companies use AI systems for cost modeling to offer better and more competitive products and services compared to the previous, resulting in a distortion of market dynamics. Consider, for example, if producers or vendors utilize AI to exchange intimate ordering information or in collusion with price estimation, it may not be fair competition and also would not break antitrust laws. Legal frameworks have to be built to govern the use of AI in competitive markets. Such frameworks should guarantee that AI technologies will not allow anticompetitive practices like price fixing or collusion to take root and flow in the automotive industry.

Figure 7: Legal and Ethical Consideration in Artificial Intelligence

5.3 Mitigating Ethical and Legal Risks

Ethical AI Design

Ethical considerations should have greater priority in the developers' system design and deployment of AI systems. Developing transparent and explainable systems in developing AI systems that are fair/accountable for making decisions. Since introducing biases in the models leads to biased results, a policy should be set forth that ethics will ensure that important biases in the models will be prevented accidentally (Ntoutsi et al., 2020). It can also help ethical training for AI developers to guarantee that relatively ethical issues, such as bias and fairness, are carefully considered before designing an AI.

Legal Framework for AI Usage

Since every company has its legal risks, it should contract a legal service to design an all-around AI framework for cost estimation to prevent any legal trouble. This framework includes meeting legal requirements, including those of intellectual property law, data protection legislation, and others. Under these standards and the law, such systems will be regularly audited.

Stakeholder Engagement

It is imperative to involve key stakeholders like suppliers, employees, and laws and regulatory bodies to mitigate ethical and legal risks. Trust develops in an AI system only when all stakeholders are in open communication and understand the risks and benefits that AI can provide before it is too late.

In developing responsible AI usage policies with input from all relevant parties, all ethical and legal concerns of all stakeholders can be addressed. AI presents a huge opportunity to transform cost modeling in the automotive industry, provided that ethical and legal factors are addressed (Weber-Lewerenz, 2021). By addressing inequality, privacy, accountability, intellectual property, and regulatory needs, companies can ensure that their AI systems are used responsibly, fairly, and legally.

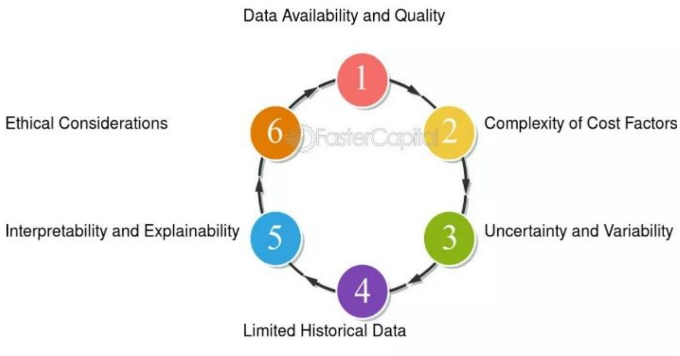

Figure 8: Limitations of AI in Cost Estimation

6. Recommendations for Future Research

Given the ever-increasing customization and concomitant low-volume production in the automotive industry, there is a need for new and more responsive ways of modeling costs, especially in automotive motor costs. There is already great potential in applying artificial intelligence (AI) to cost estimation and risk management. This section points out several interesting directions for future research to further take the cost modeling processes for customized automotive motors using AI.

6.1 AI-Enabled Collaborative Should-Cost Modeling with Suppliers

Future research on AI-enabled collaboration should include cost modeling as a key area of research that will allow automakers and suppliers to work in real-time and spend time refining or developing accurate and transparent cost models together. The cost model for suppliers is usually modeled traditionally, but those traditional methods fail due to supplier relationship dynamics, materials price dynamics, and the evolution of manufacturing processes. AI is an opportunity to cross the gaps by letting both parties input data into each other's platform and iterate.

In such a context, using AI can create an environment where the costs are predicted and actively created by the supplier and the automaker’s actuation into an ongoing process. Real-time data such as changing material prices, labor costs, supply chain disruption, and changing demand trends could be used as these platforms (Handfield & Linton, 2017). Through these means, the last step of the product cost can be driven by data and used by suppliers and manufacturers to become more transparent and build trust to streamline and achieve a more accurate cost estimation process. To address data privacy, synchronization, and interoperability issues in future research, frameworks for such collaborative platforms can be developed to handle challenges among data provided to different suppliers and used in different systems.

AI can optimize communication routes and flows when making decisions. AI algorithms could also predict how the supply chain might alter in the future and suggest proactive actions to create better cost variables for both parties, which means that when there are problems, at least they will react before they become problems. This proactive approach reduces the possibility of cost overruns and poor production planning, making production planning more efficient. The usefulness of AI for real-time collaboration, trust-based partnership development, and the introduction of predictive capability in the collaborative modeling process should be studied in future work.

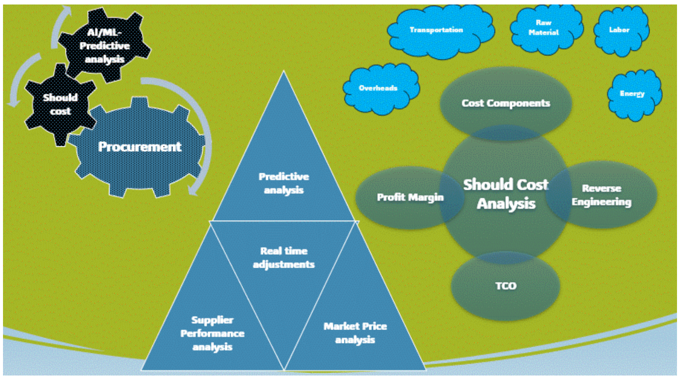

Figure 9: Empowering Procurement with AI/ML and Should Cost Analysis

6.2 Optimization of Automotive Motor Design Using AI-Based Should-Cost Models

Automobile motors nowadays are designed to combine them with cost efficiency. Future research will consider how a future AI-based cost model can help optimize motor designs considering multiple factors such as material selection, manufacturing processes, and energy efficiency. Using AI to simulate and assess the trade-offs between different designs choices, one can identify the least expensive options, allowing for the required performance characteristics.

AI-driven optimization techniques like a genetic algorithm or reinforcement learning to optimize motor designs based on cost and performance metrics would be possible. Additionally, the models could be designed to include long-term energy efficiency and operating costs (which are not solely direct costs associated with materials and manufacturing). Using AI to predict the impact of design decisions, Automakers could predict the ideal design decisions likely to affect overall costs and performance significantly, more precisely design products, reduce costs associated with prototyping the product, and shorten the product time to market.

The multi-objector optimization of automotive motors is optimized by using AI. The traditional methods of making the market are for optimizing the costs without taking action regarding energy efficiency of manufacturing, durability, and sustainability. However, if the models are based on AI, they may use holistic, sustainable design choices since they can optimize over several goals simultaneously (Zahraee et al., 2016). Future work should begin by using these multiple objectives optimization models in the design of EV motors under the cost, environmental, and performance conditions to improve the long-term viability of EVs.

6.3 Predictive Analytics for Commodity Price Fluctuations in Automotive Motor Procurement

Prediction of commodity prices that significantly affect the cost of automotive motors is another important aspect of cost modeling. Motor production costs also contain commodities, and they trade largely based on supply and demand, geopolitical tensions, and macroeconomic conditions, among other factors. African Development Bank demands it be used to predict future price movements of automobile motors, an activity beneficial for forecasted commodity price moves and their impact on the total cost of producing automobile motors.

Research in this area may also make it possible to construct predictive models based on prices, trends, markets, and external factors such as policy changes or supply chain disruption. For instance, price trends may be explicated via time series forecasting or regression models as per past data (Wang et al., 2018). Simulating different situations and assessing different levels of price volatility and how much it will cost to produce a motor is something AI can help with.

More sophisticated input or better anticipation of future cost changes could be achieved through an interface between these models and existing cost estimation systems by these automakers and suppliers. It can also help analyze procurement processes and predict when it would be appropriate to purchase the materials in advance and lock in lower prices to lessen the potential fluctuations in commodity prices. Future research will focus on applying AI to trade off dynamic procurement strategies against predictive price analytics to facilitate manufacturers' development of dynamic procurement strategies to optimally improve their procurement practices and mitigate cost risks.

6.4 AI Integration in Existing Cost Models

While AI has enormous benefits for cost modeling, many companies still rely on old costing models, such as activity-based costing (ABC) or parametric costing models. Such hybrid models can also be developed to incorporate these traditional cost models with AI to improve their accuracy and efficiency. AI can take advantage of the predictive facts of AI, while traditional models provide historical data and industry-specific knowledge.

One instance of most of this would be using AI to enhance parametric cost models by predicting future cost variability based on live data points like changes in material costs or supplier efficiency (Karwa, 2024). It is also possible for AI to tweak ABC models by enabling more precise cost drivers to be included in the model and enhance the granularity of the cost behavior across the stages of production (Khan, 2024). It is time for research in developing methodologies to seamlessly combine AI-driven predictions with our current cost estimation frameworks so the models are supported by existing practice but offer better results.

A promising alternative is constructing AI-enabled decision support tools that enable cost estimators to interact with the models and adjust familiar parameters. Such tools could reduce the distance between the standard cost estimation methods and AI models and facilitate the acceptance of AI technology among decision-makers without abandoning all that they are used to. Future research should investigate the ways of developing such decision support tools in terms of user interface and integration data model transparency, aiming that AI integration will be helpful without overwhelming the user.

Figure 10: Key Elements That Affect the Pricing Structure of AI Integration

Integrating AI in cost modeling for automotive motors is a significant step forward for automobiles ' ability to tackle the complexities of customized, allow-volume product planning in an automated, recurring way. Future research should be developed on AI-empowered collaborative cost modeling, motor design optimization, a tool for predictive analytics of commodity price fluctuations, and a hybrid AI-based model with some mix of AI and classical cost evaluation approaches. These advancements will improve the accuracy and expediency of inputting cost information and are likely to reduce risks, cut costs, and aid in better risk-taking decisions in the automotive supply chain (Cather, 2020).

7. Conclusion

The study explored AI and ML in automotive motor cost modeling for customizing and low-volume applications. Efficiently and at scale, these findings outperform the traditional cost estimation methods, although not capabilities that AI is strong at. The models presented solved automotive motor production complexity and variability in customized or low volume by using machine learning algorithms to deal with a more extensive range of input information and provide much higher flexibility. As these types of productions are dynamic, it is unfortunately impossible to adapt cost modeling using old data and fixed assumptions. This may result in inaccurate or inefficient cost estimation (Smith & Johnson, 2020). AI can have a more flexible and robust method of dealing with cost forecasting as it can look at massive data sets and identify patterns, which traditional methods would not be able to do.

This substantially reduced error rates compared to what was achieved using traditional approaches with AI-driven cost models. In particular, neural networks and random forests had improved reliability and accuracy compared to random forests and neural networks in predicting costs. These models could accommodate many of automotive motors' variables, such as material costs, design specifications, and manufacturing processes required to estimate the cost of a customized or low-volume automotive motor. The training left AI models faster over time as they got to work with more significant (and bigger and bigger) data and make predictions in real time with still very low CPU costs. Additionally, their efficiency makes them one of the most important parts of the automotive industry that always progresses, with manufacturers always creating personalized vehicles in small volumes. Scalability was one of the benefits of using AI-based cost modeling. A classic example of this is that traditional methods of cost estimation exhibit scalability problems, especially with more complex, highly variable processes. AI models are very flexible. The obvious way of extending their flexibility was to allow them to run on different motor designs and manufacturing processes, which is essential for OEMs to satisfy consumer customization requests (Singh, 2022). AI-driven models could use many data sources, including information from suppliers and market trends, to develop much more accurate and relevant cost estimates for the given production conditions.

This study brings across one important finding: the role of AI in minimizing the risk during the procurement process. There is a considerable risk in the automotive sector when purchasing a motor, including supply chain disruption, material volatility, and price volatility (Zhang & Wang, 2022). Companies can anticipate these risks by incorporating predictive analytics into AI models and anticipating an early warning, which in turn allows companies to make decisions that will minimize the impact of such disruptions. The advantage of any of these abilities lies in the fact that these companies can buy goods at lower prices and avoid the supply chain disruptions caused by the shortage or delay of the delivery of the supply chain.

Further research in this area of AI for cost modeling can consider several promising directions. The second direction worth pursuing is to build collaborative cost models that include suppliers in participation. A system of continuous collaboration between manufacturers and suppliers and the exchange of real-time data would help them make more accurate and transparent pricing. Further applications of AI-based cost models can be used to optimize motor design so that manufacturers can also make more intelligent selections of material and manufacturing processes to keep their costs lower while improving motor performance. The use of AI to predict the changes in the prices of key commodity inputs, such as copper or steel, can still be a big win when applied to predictive analytics of commodity price forecasting. The automotive industry can advance the production of customized or low-volume motors by integrating AI and ML into the cost-modeling process. The study's findings are that using AI-enabled processes improves accuracy and speed, can provide risk management in cost estimation, and can overcome procurement process problems. With the automotive industry choosing to produce more customizable and electrified vehicles, the acceptance of AI-based cost modeling will enable manufacturers to meet challenges in cost estimates and lead to more efficient and cost-efficient production systems.

References;

1. Akter, S., Dwivedi, Y. K., Sajib, S., Biswas, K., Bandara, R. J., & Michael, K. (2022). Algorithmic bias in machine learning-based marketing models. *Journal of Business Research*, *144*, 201-216.
2. Brown, A., & Davis, R. (2019). "Machine Learning for Predictive Analytics in Automotive Procurement." International Journal of Production Economics, 210, 456-467.
3. Calder, M., Craig, C., Culley, D., De Cani, R., Donnelly, C. A., Douglas, R., ... & Wilson, A. (2018). Computational modelling for decision-making: where, why, what, who and how. *Royal Society open science*, *5*(6), 172096.
4. Cather, D. A. (2020). Reconsidering insurance discrimination and adverse selection in an era of data analytics. *The Geneva Papers on Risk and Insurance-Issues and Practice*, *45*, 426-456.
5. Chavan, A. (2022). Importance of identifying and establishing context boundaries while migrating from monolith to microservices. Helina. http://doi.org/10.47363/JEAST/2022(4)E168
6. Chavan, A. (2023). Managing scalability and cost in microservices architecture: Balancing infinite scalability with financial constraints. Journal of Artificial Intelligence & Cloud Computing, 2, E264. http://doi.org/10.47363/JAICC/2023(2)E264
7. Chavan, A. (2024). Fault-tolerant event-driven systems: Techniques and best practices. *Journal of Engineering and Applied Sciences Technology*, *6*, E167. https://doi.org/10.47363/JEAST/2024(6)E167
8. Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. (2020). A survey of deep learning and its applications: a new paradigm to machine learning. *Archives of computational methods in engineering*, *27*, 1071-1092.
9. Elshawi, R., Al-Mallah, M. H., & Sakr, S. (2019). On the interpretability of machine learning-based model for predicting hypertension. *BMC medical informatics and decision making*, *19*, 1-32.
10. Felzmann, H., Villaronga, E. F., Lutz, C., & Tamò-Larrieux, A. (2019). Transparency you can trust: Transparency requirements for artificial intelligence between legal norms and contextual concerns. *Big Data & Society*, *6*(1), 2053951719860542.
11. Fraser, H., & Suzor, N. (2024). Locating fault and responsibility for AI harms: A systems theory of foreseeability, reasonable care and causal responsibility in the AI value chain. *Law, Innovation and Technology*.
12. Handfield, R., & Linton, T. (2017). *The LIVING supply chain: The evolving imperative of operating in real time*. John Wiley & Sons.
13. Javaid, M., Haleem, A., Singh, R. P., & Suman, R. (2022). Artificial intelligence applications for industry 4.0: A literature-based study. *Journal of Industrial Integration and Management*, *7*(01), 83-111.
14. Kanike, U. K. (2023). Factors disrupting supply chain management in manufacturing industries. *Journal of Supply Chain Management Science*, *4*(1-2), 1-24.
15. Karwa, K. (2024). Navigating the job market: Tailored career advice for design students. *International Journal of Emerging Business*, *23*(2). https://www.ashwinanokha.com/ijeb-v23-2-2024.php
16. Karwa, K. (2024). The future of work for industrial and product designers: Preparing students for AI and automation trends. Identifying the skills and knowledge that will be critical for future-proofing design careers. *International Journal of Advanced Research in Engineering and Technology*, *15*(5). https://iaeme.com/MasterAdmin/Journal_uploads/IJARET/VOLUME_15_ISSUE_5/IJARET_15_05_011.pdf

17. Khan, M. S. U. (2024). Exploring Theoretical Foundations of Activity-Based Costing. *International Journal of Research and Innovation in Social Science*, *8*(3s), 2953-2965.
18. Kilroy, K., Riley, L., & Bhatta, D. (2023). *Blockchain tethered AI: Trackable, traceable artificial intelligence and machine learning*. " O'Reilly Media, Inc.".
19. Klaassen, G. (2024). Confronting Bias In Artificial Intelligence: Building Transparent, Diverse, and Ethical AI Systems.
20. Kumar, A. (2019). The convergence of predictive analytics in driving business intelligence and enhancing DevOps efficiency. International Journal of Computational Engineering and Management, 6(6), 118-142. Retrieved from https://ijcem.in/wp-content/uploads/THE-CONVERGENCE-OF-PREDICTIVE-ANALYTICS-IN-DRIVING-BUSINESS-INTELLIGENCE-AND-ENHANCING-DEVOPS-EFFICIENCY.pdf
21. Kumar, A., Mishra, D. K., Upadhyay, L., Srivastava, M., & Pathak, D. K. (2023). Additive manufacturing technologies for on-demand production of personalized goods. In *Laser Applications in Manufacturing* (pp. 120-152). CRC Press.
22. Lee, H., & Kim, S. (2021). "Risk Mitigation in Supply Chain Management Using AI." Supply Chain Management: An International Journal, 26(3), 345-360.
23. Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of manufacturing systems*, *60*, 119-137.
24. Leszczyński, Z., & Jasiński, T. (2020). Comparison of product life cycle cost estimating models based on neural networks and parametric techniques—a case study for induction motors. *Sustainability*, *12*(20), 8353.
25. Lim, C. W. J., Le, K. Q., Lu, Q., & Wong, C. H. (2016). An overview of 3-D printing in manufacturing, aerospace, and automotive industries. *IEEE potentials*, *35*(4), 18-22.
26. Loyer, J. L., Henriques, E., Fontul, M., & Wiseall, S. (2016). Comparison of Machine Learning methods applied to the estimation of manufacturing cost of jet engine components. *International Journal of Production Economics*, *178*, 109-119.
27. Mbah, G. O. (2024). The Role of Artificial Intelligence in Shaping Future Intellectual Property Law and Policy: Regulatory Challenges and Ethical Considerations. *Journal homepage: www. ijrpr. com ISSN*, *2582*, 7421.
28. Mehmood, M. U., Chun, D., Han, H., Jeon, G., & Chen, K. (2019). A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. *Energy and buildings*, *202*, 109383.
29. Meyer, M. N. (2018). Practical tips for ethical data sharing. *Advances in methods and practices in psychological science*, *1*(1), 131-144.
30. Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M. E., ... & Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(3), e1356.
31. Nyati, S. (2018). Transforming telematics in fleet management: Innovations in asset tracking, efficiency, and communication. International Journal of Science and Research (IJSR), 7(10), 1804-1810. Retrieved from https://www.ijsr.net/getabstract.php?paperid=SR24203184230
32. Olaleye, I. A., Mokogwu, C., Olufemi-Phillips, A. Q., & Adewale, T. T. (2024). Optimizing procurement efficiency: Frameworks for data-driven cost reduction and strategic vendor management.
33. Olateju, O., Okon, S. U., Olaniyi, O. O., Samuel-Okon, A. D., & Asonze, C. U. (2024). Exploring the concept of explainable AI and developing information governance standards for enhancing trust and transparency in handling customer data. *Available at SSRN*.
34. Pellegrino, R., Costantino, N., & Tauro, D. (2019). Supply Chain Finance: A supply chain-oriented perspective to mitigate commodity risk and pricing volatility. *Journal of Purchasing and Supply Management*, *25*(2), 118-133.
35. Raju, R. K. (2017). Dynamic memory inference network for natural language inference. International Journal of Science and Research (IJSR), 6(2). https://www.ijsr.net/archive/v6i2/SR24926091431.pdf
36. Sadrabadi, M. H. D., Makui, A., Ghousi, R., & Jabbarzadeh, A. (2024). Designing a green-resilient closed-loop supply chain to preserve business continuity under interrelated disruptions (a case study of the automotive battery industry). *Computers & Chemical Engineering*, *185*, 108675.
37. Sappa, C. (2019). How data protection fits with the algorithmic society via two intellectual property rights–a comparative analysis.
38. Singh, V. (2022). EDGE AI: Deploying deep learning models on microcontrollers for biomedical applications: Implementing efficient AI models on devices like Arduino for real-time health monitoring. International Journal of Computer Engineering & Management. https://ijcem.in/wp-content/uploads/EDGE-AI-DEPLOYING-DEEP-

LEARNING-MODELS-ON-MICROCONTROLLERS-FOR-BIOMEDICAL-APPLICATIONS-IMPLEMENTING-EFFICIENT-AI-MODELS-ON-DEVICES-LIKE-ARDUINO-FOR-REAL-TIME-HEALTH.pdf

39. Singh, V. (2023). Federated learning for privacy-preserving medical data analysis: Applying federated learning to analyze sensitive health data without compromising patient privacy. International Journal of Advanced Engineering and Technology, 5(S4). https://romanpub.com/resources/Vol%205%20%2C%20No%20S4%20-%2026.pdf
40. Smith, J., & Johnson, L. (2020). "AI in Cost Estimation: A Review." Journal of Manufacturing Systems, 45, 123-135.
41. Wang, B., Liu, P., Chao, Z., Junmei, W., Chen, W., Cao, N., & Wen, F. (2018). Research on Hybrid Model of Garlic Short-term Price Forecasting based on Big Data. *Computers, Materials & Continua*, *57*(2).
42. Wang, Y., Ma, H. S., Yang, J. H., & Wang, K. S. (2017). Industry 4.0: a way from mass customization to mass personalization production. *Advances in manufacturing*, *5*(4), 311-320.
43. Weber-Lewerenz, B. (2021). Corporate digital responsibility (CDR) in construction engineering—ethical guidelines for the application of digital transformation and artificial intelligence (AI) in user practice. *SN Applied Sciences*, *3*, 1-25.
44. Wu, P. H., Aroush, D. R. B., Asnacios, A., Chen, W. C., Dokukin, M. E., Doss, B. L., ... & Wirtz, D. (2018). A comparison of methods to assess cell mechanical properties. *Nature methods*, *15*(7), 491-498.
45. Yang, P., Xiong, N., & Ren, J. (2020). Data security and privacy protection for cloud storage: A survey. *Ieee Access*, *8*, 131723-131740.
46. Yilmaz, M. (2015). Limitations/capabilities of electric machine technologies and modeling approaches for electric motor design and analysis in plug-in electric vehicle applications. *Renewable and Sustainable Energy Reviews*, *52*, 80-99.
47. Yin, Y., Stecke, K. E., Swink, M., & Kaku, I. (2017). Lessons from seru production on manufacturing competitively in a high cost environment. *Journal of Operations Management*, *49*, 67-76.
48. Zahraee, S. M., Assadi, M. K., & Saidur, R. (2016). Application of artificial intelligence methods for hybrid energy system optimization. *Renewable and sustainable energy reviews*, *66*, 617-630.
49. Zhang, Y., & Wang, X. (2022). "Optimization of Electric Motor Design Using AI-Based Cost Models." IEEE Transactions on Industrial Informatics, 18(4), 2345-2356.