Transportation Research Part E

Application of Blockchain and Smart Contracts in Autonomous Vehicle Supply Chains: An Experimental Design

--Manuscript Draft--

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Abstract:	With the rise of digital sustainable business models in the Autonomous Vehicles (AV) industry, the traditional automakers are undergoing a major restructuring in their key performance areas and associated supply chains processes. Focusing on an innovative AV design (AD) concept, this paper investigates how Artificial Intelligence (AI) and Blockchain-based Smart Contracts can enhance sustainable supply chain operations. A novel design element, Margin Indicator (MI), is developed to obtain reliable predictive analytics results from the mainstream machine learning algorithms. The proposed approach supports a robust control of costs and energy, while maintaining a high level of transparency in managing decentralized AV supply chain processes, monetary impacts, and environmental sustainability. Testing the developed concept through a preliminary case study, we observed a reduction in energy wastage and hidden financial transactions by 12.48% and 11.58%, respectively. Supported by blockchain and AI, the developed framework is expected to offer an improved product traceability, transaction transparency, and sustainable economic growth for the AV supply chains.
Response to Reviewers:	Response Letter Transportation Research Part E Manuscript Number: TRE-D-22-00072R1 AI-enabled and Blockchain-based Smart Contracts for Sustainable Autonomous Vehicle Supply Chains EIC: I have completed my evaluation of your manuscript. Your paper is conditionally accepted. Please improve it with the advice of the review team (English and exposition). Moreover, nowadays, I would request authors for technical papers in logistics/supply chains/operations management to pay attention to the following when they revise the paper/prepare the final version: Guest editor: The authors have made great efforts to improve the work by addressing reviewers' comments. Two of the reviewers have recommended the acceptance of this work and one of them has suggested that the paper should be further polished. Hence, I recommend a conditional acceptance of this paper. Please check the language, equations and references to make it typo free. Thanks. [Author Response]: We wish to express our gratitude to the EIC, Guest Editor, and all Reviewers, whose thoughtful comments and insights assisted us in undertaking the necessary additional works. All comments were considered carefully to improve this version of our manuscript. We are confident that this version is in a much better shape. All your comments were incorporated in this revised version. Here is the summary of actions taken in this revision: a)Some new recent references were added especially in Section 2.1, Section 7 and 8 to highlight the importance of blockchain in the area of logistics and supply-chain.

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"8. Theoretical and Managerial Implications
The present work contributes to the sustainable logistics and AV supply chain literature by focusing on the design, manufacturing, assembly, and transportation processes. Key theoretical implications of the present study are:

•The present study can trigger new intervention-based validation studies in process restructuring and design environments beyond the AV domain (Hedenstierna et al., 2019; Tao et al., 2020) and provide experimental evidence for digital encapsulation in a blockchain-based smart contract environment (Holmström et al., 2019).

•The proposed design method uses IoT-enabled smart devices and embedded components and captures real-time data for design, modeling, analysis, training, and evaluation. Both SVML and K-Mean clustering ML models provided cost estimation, product condition summary, and energy calculations. Thus, the study deliberations advance the research discussions leading to integrating ML models with the design phase and operations, articulating their real-time usage in energy management, cost modeling, and inventory movements. It can also prompt the deliberation for new performance metrics, which can be integrated into sustainable supply chain frameworks.

•The study also triggers research interest and focuses on ranking and assessing the key sustainability risk factors that can easily be customized within the AI-enabled environment across supply chains. It may trigger new theories and business models, especially in the sustainable logistics domain. For instance, highlighting the role of customizable technology-oriented policies in AV design, the present study sets a new benchmark for advancing modeling and design in the field of sustainable logistics.

In addition, the present research offers several managerial implications that can benefit the supply chain and logistics operations managers.

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•Compared to the current AV development practices, the proposed MI helps to reduce ambiguity, uncertainty, and complexity of operations, while assessing energy and market conditions (Niu et al., 2022). This leads to sustainable socio-economic balance with reliable business practices by minimizing the trade-off risks between different factors (e.g., cost and energy). This would help supply chain managers to make more robust energy and cost-based sourcing and logistics decisions, enabling them to mitigate supply chain sustainability risks (Cao & Shen, 2022) and achieve logistics efficiency in sustainable environments.

•The study deliberations help to reduce the influence of third parties and provide a better control of the supply chain processes, ensuring real-time data sharing among stakeholders. This transformation helps managers to control the AI/blockchain-enabled production environments by integrating real-time stock prices and brokerage. Hence, industrial automation policies and regulatory guidelines inform the design of either application logic contracts (work by validating the communication between devices through blockchain) or smart legal contracts (with the legal remedy in case stakeholders do not fulfill their obligations), which may consider transport mode and warranty clauses.

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•Finally, our experimental findings and novel AD would help the part manufacturer to chart action plans of productions, transportation, distribution, or any sort of omnichannel activities in advance without bias in the working conditions. The findings of this design articulate the urgent need for applying smart technologies which help the industry, including reverse logistics and wastage scrapping procedures, by making the process leaner and greener. With these extended scopes, unbounded controlled decisions and qualitative managerial flexibility can be achieved in all aspects of supply

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Cover Letter

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Sydney

La Trobe Business School
Department of Management & Marketing

20/07/2022

Dear Prof. Jason Choi,

I am pleased to inform you that the manuscript has been successfully revised according to the Editors' and 2nd Reviewer's. Please find enclosed the detailed responses to the reviewer and the revised version of manuscript entitled "*Application of Blockchain and Smart Contracts in Autonomous Vehicle Supply Chains: An Experimental Design*".

We thank You, the GE, and the Reviewers for their insightful comments and for helping us in improving our paper for possible publication in the special issue of TRE on "*Sustainable logistics and supply chain management in the blockchain era*".

I hope you and the TRE team find this paper satisfactory and look forward to hearing from you.

With my best regards,

Sean Arisian PhD, PEng
Program Director: Logistics & Supply Chain
La Trobe Business School, La Trobe University, Melbourne, Australia
Profile: https://scholars.latrobe.edu.au/display/sasian

Response Letter

Transportation Research Part E

Manuscript Number: TRE-D-22-00072R1

AI-enabled and Blockchain-based Smart Contracts for Sustainable Autonomous Vehicle Supply Chains

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Highlights:

- An innovative AV design using Artificial Intelligence and Blockchain-based smart contract is proposed
- A novel design element, Margin Indicator, is incorporated into the proposed AV design
- The proposed approach supports a robust control of costs and energy by reducing energy wastage and hidden financial transactions
- The proposed framework offers an improved product traceability, transaction transparency, and sustainable economic growth for the AV supply chains

Title Page (with Author Details)

Application of Blockchain and Smart Contracts in Autonomous Vehicle Supply Chains: An Experimental Design

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Application of Blockchain and Smart Contracts in Autonomous Vehicle Supply Chains: An Experimental Design

Abstract

With the rise of digital sustainable business models in the *Autonomous Vehicles* (AV) industry, the traditional automakers are undergoing a major restructuring in their key performance areas and associated supply chains processes. Focusing on a novel AV design (AD), this paper investigates how *Artificial Intelligence* (AI) and Blockchain-based *Smart Contracts* can enhance sustainable supply chain operations. A novel design element, *Margin Indicator* (MI), is developed to obtain reliable predictive analytics results from the mainstream machine learning algorithms. The proposed approach supports a robust control of costs and energy, while maintaining a high level of transparency in managing decentralized AV supply chain processes, monetary impacts, and environmental sustainability. Testing the developed concept through a preliminary case study, we observed a reduction in energy wastage and hidden financial transactions by 12.48% and 11.58%, respectively. Supported by blockchain and AI, the developed framework is expected to offer an improved product traceability, transaction transparency, and sustainable economic growth for the AV supply chains.

Keywords: *Digital Supply Chain, Blockchain, Smart Contract, Artificial Intelligence, Autonomous Vehicle, Sustainable logistics.*

1. Introduction

Blockchain technology and smart contracts have proven capable of creating and empowering self-sustained business models that can withstand supply chain uncertainties and environmental adversities. Development and application of modern smart tools can enhance domain-specific expertise and dedicated technology-driven working platforms within the digital supply chains (Dolgui et al., 2020; Liu et al., 2020). Some technologies involve a combination of *blockchain* and *machine learning* (ML) models to offer operational directions based on data patterns. They also employ the *Internet of Things* (IoT) to leverage the internet and data-based services, and use built-in mechanisms, such as *embedded process automation*, which drives operational excellence and ensures tamper-proof data management.

Leading manufacturing firms such as Ford, GM, Renault, and BMW have recently set up a blockchain consortium to facilitate cross-functional and industry collaborations, ensuring information consistency and setting high level industry standards (Manimuthu et al., 2021a,b: Narayanan et al., 2020). Such initiatives help optimize resource utilization and achieve process efficiency in manufacturing, quality, distribution, and cost management in real-time. Amidst these developments, industries advance through blockchain-based innovations in conjunction with robust design interventions to improve their supply chain efficiency, extending the boundary even to the spare parts supply chains (Chandrasekaran et al., 2020; Hasan et al., 2020; Malhotra et al., 2022). Such advancements focus on process optimization while also managing overall cost margins in individual operations, productivity, and market value enhancement (Shi et al., 2020), efficient data-driven decision-making (Tao et al., 2020), and offering critical inputs to financial planning.

Motivated by these trends, the present experimental study aims to deploy new intelligence models together with blockchain-based smart contracts (i.e., *a self-executing mechanism directed by codes between the stakeholders*) in the automobile industry for three main reasons (Cai et al., 2021; Choi et al., 2020a). *First*, the current industry practices involve critical parametric evaluation for energy consumption, cost functions, and hidden brokerages. Highly subjected to market uncertainty (Reza-Gharehbagh et al., 2022), these practices show inconclusive evidence of their operational impact in the literature, and the latest technologies do not capture them comprehensively under blockchain environments (Choi et al., 2020a,b; Kouhizadeh et al., 2021). *Second*, calibrating results based on process evaluation and work procedures impacts risk assessment and quality control checks, especially in energy, manufacturing, and automotive industries. Overlooking such unpredictable risk factors may lead to significant losses. This is not adequately explored in prior studies and, hence, the literature does not offer sufficient evidence. *Third*, the literature lacks deliberations around AI/blockchain integrated error rectification schemes or mechanisms for self-sustainable operational excellence (Grover et al., 1995; Hasan et al., 2020; Mendoza et al., 2016). In parallel, prior research recommends the use of domain-related pervasive computing and solicited organizational procedures at all stages to achieve standalone solutions in real-time. Although many companies are keen to adopt AI and other smart solutions, potential use cases and benchmark models are limited. Also, infrastructure support and stakeholder interest restrict deployment of effective integrated models (Ivanov et al., 2019).

Recently, the interest in autonomous vehicles (AV) (i.e., autopiloting to predetermined destinations without, or with less, human intervention) has become topical for new technology development studies (Van Brummelen et al., 2019). The associated AV design (AD) domain has focused on supply chain processes, aiming to leverage the data power and seamlessly integrate multiple components, such as ML and blockchain, into the industrial systems (Manimuthu et al., 2021b). However, research remains far from reporting the integration of those components in the vehicle design stage. Thus, to address the identified operational gaps in the context of AD, the present study proposes a unique design intervention framework and aims to answer two questions:

1. *How can firms conceptualize and develop an AI/blockchain-based AV from a smart contract perspective?*
2. *How can firms achieve self-sustainable and reliable operational and business practices using innovative IoT-assisted machine learning models?*

The research is grounded on the explanatory power of intervention-based research (IBR) and business process reengineering (BPR) for AI-based modeling and design integration, test cases, and validation (Chandrasekaran et al., 2020). This paper offers several contributions to the practice and literature. *First*, this pioneering experimental study deliberates on the need for AI-based models that aim for operational efficiency in the AV sector. The study introduces a novel metric, *margin indicator* (MI), to assist AV design development. The MI enumerates the excessive usage of individual indicators, such as costs, energy, tools, and supplies. It reduces losses incurred by firms by forecasting and predicting the active requirement values. By setting a threshold value for the critical factors (e.g., cost, energy, stock pricing, EOQ, and other quantitative losses during transportation and delivery), the MI can help top management monitor and strategize their inventory movements, hidden brokerages, excess energy, and costs and make essential decisions in real-time. *Second,* this study explains how blockchain helps organizations achieve standardized goals and business excellence by abiding with their existing regulatory policies and operating guidelines. Our results from the pilot study show an 11.58% increase in profit and a 17.2% rise in sales margin. *Third,* the study presents an automated and self-sustainable smart design that underlines the need for a smart IoT-based ecosystem in the AV manufacturing, production, and supply chains. The design involves smart contracts that actively help the logistic and supply chain managers simply redesign and incorporate the MI into their operating procedures.

The remainder of this paper is structured as follows. Section 2 reviews the literature on s*mart contracts* in industrial practices and the importance of AI in operations and business management. Section 3 discusses the AD developed and its attributes that help in finding desirable MI target values. Section 4 discusses the methodology and operational procedures involved in the AV design. A case study with a business model is presented in Section 5. The key experimental findings, modeling, and design results are detailed in Section 6. Section 7 discusses the main findings and Section 8 provides theoretical and managerial implications. Section 9 concludes the work by listing limitations and suggesting a future research agenda.

2. Literature review

The section discusses the sustainable supply chains and the role of AI/Blockchains with smart contracts, followed by automation in the industry. Then, the relevance of intervention-based research and process reengineering to this research is established, and finally, the section summarizes the study gaps.

2.1. Sustainable supply chains and AI/blockchain technologies

Driven by the sustainable development goals, leading firms have begun to adopt innovative tools that enable them to achieve operational excellence, while addressing the pressing sustainability issues (Saberi et al., 2019). It is a firm and industry level mandate that focuses on digitization, encouraging firms to use advanced technologies (such as blockchain and artificial intelligence) in different operations and enhance their automation maturity level. On the other hand, intra- and inter-organizational levels suggest the encapsulation of data and processed digital information required (Holmström et al., 2019). Such initiatives facilitate data transparency for all stakeholders, an essential requirement of sustainable supply chains (Sanders et al., 2019).

Recent years have witnessed inter-disciplinary efforts to deliberate and offer comprehensive solutions to such sustainability challenges. In a review study, Park and Li (2021) report the trend of technology convergence in driving the sustainability agenda. This development envisaged new operations models, especially developed for the design, inventory, and logistics functions of supply chains. These operations models support cloud-based service platforms and a digital mobility ecosystem that automates all possible transactions from product design to consumption, aiming to reduce the probability of common errors (Holmström et al., 2019; Koh et al., 2020). Such initiatives directly or indirectly promote sustainability objectives at the firm and industry levels.

Blockchain and AI are among the key technologies that have proven capable of driving sustainable operations. While the former facilitates smart contracts for supplier relations, the latter focuses on the data capabilities through IoT and machine learning-based predictive modeling. They have the power to register and distribute the transactions, including material flow information, order tracking (related to payments, receipts, and invoices), and digital asset operations, including warranties, certificates, licenses, and copyrights, in a unified but decentralized manner (Karakas et al., 2021). These innovative data-based mechanisms create win-win situations and warrant a high degree of integration and trust among stakeholders. They also make significant impacts on sustainability, by offering new insights into the stakeholder challenges, coding material consumption patterns and cost savings, and reduced lead-time with improved responsiveness (Reyes et al., 2020). For instance, insights drawn from blockchain offer a scope to supply chain planners to strategize and optimize their inventory and logistics operations with cost and energy savings, contributing primarily to the economic and environmental agenda. To achieve these goals, it is essential for firms to analyze, predict and forecast their product requirements (including design process-related information) and preferences, market risks, including social indicators, and minimize variations in the delivery. Besides their advantages, Koh et al. (2020) argue that these technologies are not meant to replace the physical technologies; instead to act as proof of work to make smarter decisions and enhance sustainable performance. So, poor implementation of these technologies due to inconsistencies in standards, definitions, usage patterns, and languages may even worsen the supply chain performance (Sodhi et al., 2022). Nevertheless, denying and delaying digital adoption and smart transitions may harm the industry's overall performance (Choi & Siqin, 2022).

As the smart concepts evolve, the techniques and methodologies for design, analysis, testing, evaluation, and decision-making need to be more sustainable and resilient in real-time (Bonawitz et al., 2019; Manimuthu & Ramadoss, 2019; Saberi et al., 2019). Debugging, logging, processing, and real-time mapping are undeniable focus areas where data is generated in bulk. These data are resources that provide insights into performance and other key management decisions, and they need to be managed efficiently to improve throughput and attribute-based qualitative outcomes. Thus, sustainable digital transition models have become inevitable in organizational success, and their adoption is of growing interest to smart supply chain leaders. Moreover, AI-driven supply chain practices can improve energy management leading to process automation and energy efficiency. Thus, production control tools and algorithms play a critical role in ensuring sustainable operations in a smart ecosystem (Woerner et al., 2022).

To achieve a sustainable technology solution, enterprise systems must be fit, flexible, and customizable to meet industry needs (Mohanta et al., 2020). Smart contracts are the self-executing computer protocols in a blockchain environment that facilitate verification and enforcement of contract standards (Governatori et al., 2018). They govern all processes with the stakeholder or participating agents' consensus in a public or private blockchain environment. *Ethereum*, *Polkadot*, *EOS*, *Binance Smart Chain*, and *Solana* are the prominent blockchain environments that host smart contracts and are validated by the distributed consensus. Smart contracts of manufacturing manage inventory specifications, such as quality parameters, quantity ranges, and services, cover the part of their governance and support event-based logistics functions promoting supply chain transparency (Koh et al., 2020). These reduce the third-party interventions and integrate sensor-based information to automate relevant supply chain processes. They provide a radical change in the international business by reducing paperwork, increasing the pace of transactions, and bringing cost efficiency by ensuring the successive tracks instead of a single-tract contract (Salmerón-Manzano and Manzano-Agugliaro, 2019).

A recent review study by Xu and He (2022) revealed a notable trend of managing product distribution through the blockchain technology. Some recent studies also detailed the importance of smart logistics and distribution of goods and services with the help of blockchain based system (Deepa et al., 2022; Jabbar et al., 2022; Zhu et al., 2022). From the existing methods and experimentations, conclusive evidence on blockchain applications can be correlated with the smart logistics practices that results in improved performance both in process design and control (Choi & Siqin, 2022; Li et al., 2022) as well as decentralized distribution systems (Deepa et al., 2022). Recent studies by Abdel-Basset et al. (2021) and Baygin et al. (2022) revealed that the way blockchain technology handles data privacy and security during real-time supply chain operations is still a major concern to many stakeholders (Abdel-Basset et al.,2021; Baygin et al., 2022). Overall, blockchain-enabled systems are recognized as one of the promising technology inclusions in digital supply chains, ensuring data transparency with minimum errors. The associated integration and design issues, however, may limit their usage. As can be seen, while the prior studies offer scope to explore key design components of blockchains, such as brokerages and energy utilization, only a few research studies link operational efficiency and design development. Table 1 in the Appendix summarizes the existing literature on the use of blockchain and AI in supply chain practices.

2.2 Process automation

Firms often find it challenging to streamline their supply chain operations when there is no underlying guideline and regulatory policy to control, monitor, or coordinate the suppliers' activities. Companies now actively adopt process automation practices to empower and support their supply chains to perform more effectively (Manimuthu et al., 2020). Rather than concentrating on developmental plans, firms are actively considering revamping their design and digital operations to enhance productivity in the long run. Process automation plays a critical role in enhancing the overall business performance, supporting sustainable operations, and ensuring competitiveness of the associated supply chains in the global market. Additionally, any new innovation may influence energy, cost, valuations, and market risks which affects hidden brokerages and energy wastages and the firms' overall performance (Rajeev et al., 2017).

In order to resolve the overall cost and energy variations in automated operations, regulatory policies, and industrial norms are introduced to comply with industrial guidelines and rules. Management regulations and detailed guidelines (e.g., risk assessment, component control, goods movements, operational policies, transportation, vehicle movements, loading and unloading, delivery, and storage) need to be disseminated to all active participants and properly monitored (Manimuthu et al., 2021a,b). This evolution helps stakeholders closely monitor the operations, performances, and product movement without the interventions of unknown players or encouraging hidden claims or charges that affect the production costs and energy usage (Javadi et al., 2019; Naclerio & De Giovanni, 2022). Calculated performance measurements and their outcomes can be visualized by engaging a series of automation processes in real-time. These automation and monitoring procedures can revoke any form of misguided, masked, or counterfeit operations (Kouki et al., 2020).

Transformations in terms of Industry 4.0 (Wang et al., 2020b) and transitions such as embedded smart connectivity and communications and sensor-based operations have become more resilient and can assist in smooth operations of the industry. As a key element in successful smart operations modeling, AI models evolve in tandem with the changes implemented in the industrial environment (Rahimi et al., 2021). The surge in *smart equipment*, *enterprise systems*, and *robotic process automation* (RPA) models leverages the use of AI models in any workplace (Rajeev et al., 2017). Almost all operational areas within supply chain practices can be efficiently managed using customized AI models. In the conditional operation scenarios, the decentralized and standalone AI models can be linked with any desirable supply chain processes. Such self-centered sophisticated AI models enable the stakeholders, end-users, and investors to closely monitor the supply chain performance in real-time.

Additionally, with the growth of AV and the alternate energy sources, the domain is topical for integrating advanced technologies such as AI and ML techniques in design and manufacturing operations. Such integration enables product tracing and ensures system efficiency, maintenance, and secure operations in real-time (Martins et al., 2020). From the extant review, our survey outlines the need for an experimental study that considers AI-based models in an AV environment using smart contracts. The critical task of such AI-driven practices is to develop a working policy that enables firms to apply essential design interventions that support future sustainable supply chain operations.

2.3 Intervention-based research (IBR)

The intervention-based research approach is an emerging paradigm that mandates design changes with *context-intervention-mechanism-outcome* (CIMO) logic and proposes new technical solutions (Chandrasekaran et al., 2020). It supports developing new designs through logical reengineering to gain real-time operational insights (Hedenstierna et al., 2019). The approach demands a high level of data accessibility to stakeholders of design interventions. For example, in evaluating the purchase of intelligent sensors, the IBR demands access to cost details in quotations, market prices, and other commercial data, such as lead time and inventory, including economic order quantity values (Anand et al., 2021). Figure 1 below depicts intervention stages, where key insights and other procedural changes are instantly shared between multiple internal stakeholders (Hedenstierna et al., 2019). Although firms' operational ecosystem may constrain the project charter, the IBR approach allows them to achieve maximum design potential through robust validation procedures (Chandrasekaran et al., 2020).

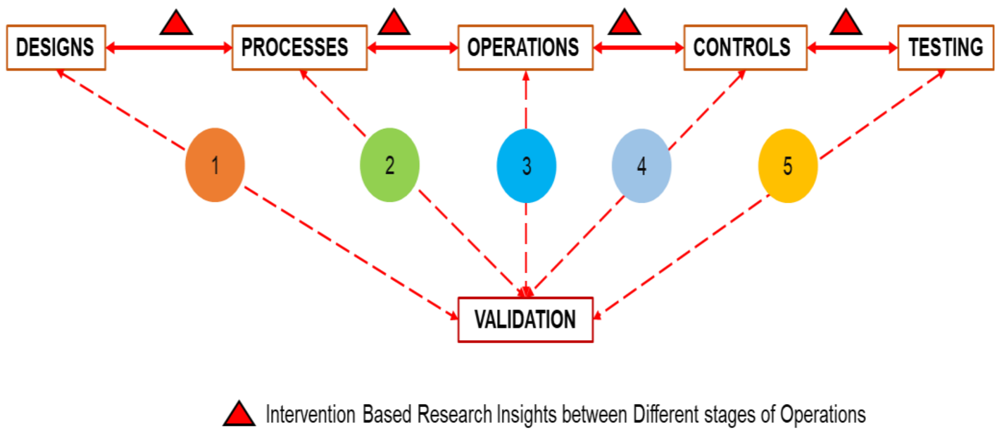


Figure 1: Intervention-based research in industrial operations

2.4 Business process reengineering (BPR)

The BPR primarily focuses on the process design in operations and business transformations in the existing smart/automated work environment. The approach involves a series of process-focused steps such as:

- Identification of critical zones;
- Review of the existing mechanisms and operating procedures;
- Generating design ideas and intellectual overviews;
- Testing the developed methods and process transition ideas;
- Evaluation of the proposed models and methods; and
- Implementing the workplace after successful testing and evaluations.

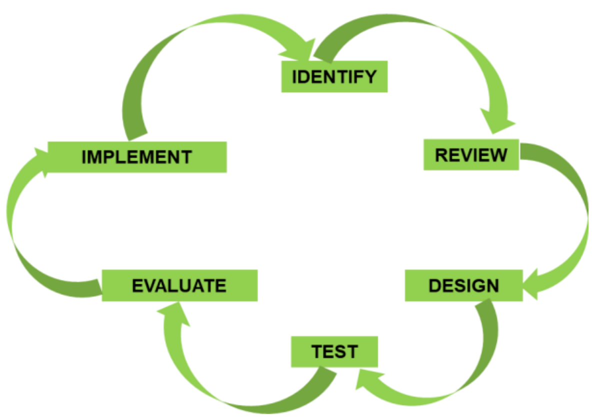


Figure 2: Operations flow in business restructuring

These steps are customizable depending on the business requirements and infrastructure support. The BPR approach helps firms critically evaluate hidden operating procedures, while trading off with the overall operating mission of manufacturing firms (Palma-Mendoza et al., 2014). Figure 2 depicts the key re-engineering steps. The growth of ERP and RPA triggers the AI models to leverage the organizational level data. They integrate robust ML algorithms to propose new metrics and normalization attributes for validating the current and newly developed design models in real-time. Thus, the power of BPR and IBR provides a suitable ground to gain insights into design reengineering, make performance improvements through AI/ML integration, and evaluate critical processes by offering new perspectives to the AV domain. More specifically, they support and advance the reengineering of the cost and energy management processes in real-time.

2.5 Research gap

The extant literature also supports mapping and risk modeling in the AV due to unstable logistics, operations, and supply chain practices. Uncertainties in the inventory distribution potentially impact the final product delivery, irrespective of consumer demands and market values (Gualandris et al., 2021). Thus, our review supports the need for restructuring business operations by integrating the core metrics such as manufacturing costs, energy consumed, and market prices. This is the critical requirement to monitor and strategize key industry parameters. However, the literature lacks any deliberation on the AI-enabled integrated core evaluation criteria with the evidence of a working model and design of blockchain-based smart contracts focusing on capturing process-level data and sharing them with inter-and intra-firm actors (Holmström et al., 2019; Koh et al., 2020).

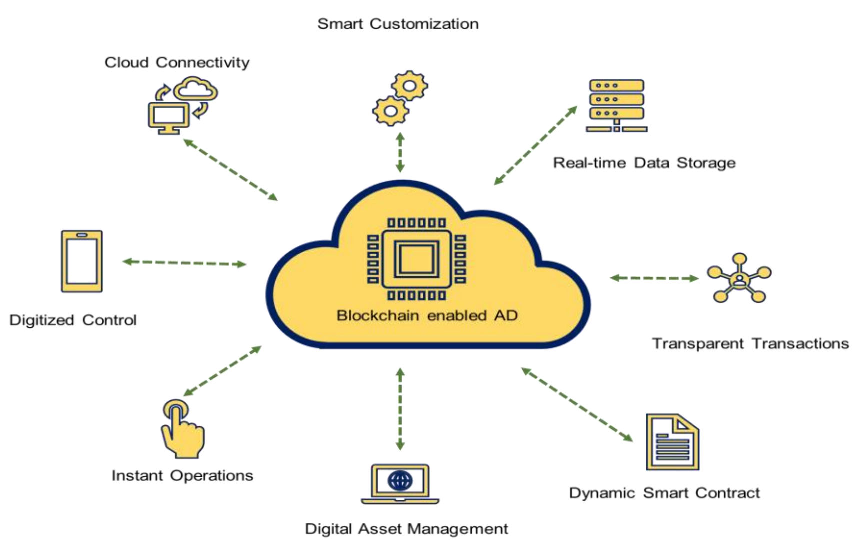


Figure 3. Practical use-cases and impact of blockchain-enabled AD

To bridge the research gaps, we focus on a case study and follow the IBR and BPR theories to identify and integrate key hidden yet crucial elements that impact robust design and operational efficiency. Using a hybrid AI and blockchain-based redesign solution (Singh et al., 2020), we investigate the benefits of applying smart embedded sensors, high-level machine learning algorithms, as well as decentralized and distributed s*mart contracts* in the AV supply chains. As AD has several inbuilt automation tools, AI models, and a series of customized process control procedures, the industry's productivity and performances are enhanced in several ways, with particular attention to costs and energy management, as shown in Figure 3.

Some of the key contributions include:

1. Automated control and decentralized monitoring mechanism for all the individual sections within the industry;
2. A flexible smart contract under mutual grounds from all participating investors and stakeholders;
3. Transparent financial transactions with a specific focus on energy and cost management;
4. Unconditional smart monitoring feature from the system level throughout the products' final delivery; and
5. Supply-shock management in both the supply chain and logistics practices makes the entire operations and control system operate in a stable and sustainable environment.

As expected, our results confirm that hidden financial transactions, time-based inventory, supplies delivery, and energy utility involved in the design and development of AV can be easily identified. Predictive analytics can also be integrated with the proposed design method. These approaches will ensure transparency in the AV industrial operations resulting in productivity enhancements. Deliberate conditional restructuring in the industry using the AD developed has significantly demonstrated several positive impacts, including energy wastage mitigation and unusual monetary transactions. Stakeholders and retail investors acquire every detail of the transparent operations by using AD in their industry practices.

3. Modeling & Design

In this section, a highly sophisticated AV Design (AD) is developed to ensure enhanced product traceability, quantitative transactions transparency, and sustainable economic growth for the AV companies in real-time. A novel data-driven threshold value, *Margin Indicator (hereafter, MI)*, is used in the decision-making analysis in the AD model developed. Actions are taken without any intervention or restructuring during the initial operational stages. This is to analyze and identify the level of restructuring required to be implemented in the design. The preliminary finding will be logged and evaluated to understand the behavior of the multiple systems involved in the industrial procedures. All these are aligned and studied with the prevailing regulations from which the key insights about the following steps are correlated and studied: *Ordering->Vendor*

Details->Loading & Unloading->Modeling->Control->Processing->Analysis->Testing->Training->Validation->Result implementation.

Data generated from every stage of operation are closely modeled using suitable machine learning models. Since the automobile manufacturing and assembling unit stages involve heavy equipment and robotic processes, semi-supervised ML models are used in data processing and analysis. Data acquired from the embedded sensors and hardware-in-loop designs are modeled and analyzed for integrity, and validated using the quoted regulatory principles in real-time. This involves licensing, market pricing, delivery charges, brokerages, loading and unloading cost, and energy involved for delivery and transportation. In the AD developed, support vector machine learning (SVML) quantifies data, and K-mean clustering is used for data categorization and model analysis. These assist in developing an unbiased smart contract that all the industrial shareholders accept without further modifications. Another reason for selecting the K-mean ML technique is its robustness in similarity identification and processing of the unlabeled data received from all individual suppliers and vendors. Unlike traditional methods of calculation and interpretation, it is possible to add weights and graphs to the received values, which helps to categorize them during the model analysis and valuation procedures (Manimuthu et al., 2021a,b). Section 4 provides more details on the technique.

Often, the system requires time-bounded critical data processing and testing from different sections in the industry, such as inventory, logistics, and warehousing functions. Thus, regression methods are used in those areas where the difference in multiple vendor details and products or the proportion of items are identified. The training model involves independent and dependent variables and critical cost and energy parameters. For the analysis and margin value findings, the whole process of industrial operations is categorized into three groups: 1. *Cost Evaluation, 2. Transportation, 3. Energy Evaluation and Management*. Each operations group is modeled separately to identify the optimum margin value indicators for all goods and supplies required for the automobile design and development. Details of the proposed model, including mathematical notations and expressions used for modeling and estimating the values for various critical parameters (essential for MI value estimation in AD modeling), are provided in the Appendix.

4. Design methods and stages of operations restructuring

The AD developed has preliminary evaluations and data insights from all key critical sections in the automobile unit. These sections include loading, assembly, distribution, transportation, and a few other sections where occasional modeling and redesign are propagated. In the long run, evaluating and modeling all the sections is mandatory as the data and embedded components involved in the distribution and processing increase exponentially. Policy changes are made before the processes are modeled and are designed to adopt smart contracts in the design phase. This supports the implementation procedures where the involvement of every individual agent is essential in the energy and cost evaluation subjected to market risk and share values in real-time. Segregating all operations and multiple zones involved in the complete product design into a compartment/zone for easy identification and interpretation assists the ML models in finding the accurate MI range for every element involved in the design. Each of the categorized compartments is unique and interconnected. Data are shared with other zones in case of any redesign and interventions in the design or modeling required for smooth operation. These zones are as follows: *Design->-Process>-Operations>-Testing->Control.* The zones that focus on reengineering in the event of interventions are identified, causing potential improvisation in the overall performance of the supply chain processes during the modeling, testing, assembling, and delivering the vehicle to the commercial market.

4.1. Stage 1: Design

As the design includes data-driven decision-making and process control, embedded devices installed in the automobile industry are relied on for data-related insights. For that objective, data pooled from participating agencies, such as vendors, suppliers, short-term service providers, and embedded device agents, are modeled and stored with their unique identification details. These data pre- and post-processing will be conducted during the model training and validation. Any mismatch or errors during the application of IBR methods, and the actual data will be mined out and re-engineered using the latest values. Materialized values will be considered as the input *algorithm* for model training and data insights. Warranty details, licensing data, and contract duration are analyzed in the training phase, mainly SVML. This is because, for each component or device in the design, many suppliers are available, and their priority is modeled based on the best market price for the product and the consumer's preference of choice. This resource mapping is imperative for model training and vector calculations.

Loading and unloading time of data are also part of this mapping procedure. The entire data modeling and device data management are elucidated by the trust-based vendor management and goods supplies, and they demand the original details furnished by the participating agents during automobile manufacturing. Once the process is completed, these values are mapped with their designated classifiers and respective sections. All the mapped data are correlated with MI values for the AD modeling throughout the studies. Any improvisation identified using these values will be immediately pulled out from the stack and analyzed for risk assessment, trust management, and s*mart contract* valuation before the final product delivery.

4.2. Stage 2: Process

Mapped data are processed and shared with the next stage of AD modeling. During this process stage, clusters formed with the available data are mapped with their respective suppliers, and the stock values are correlated with their existing records and s*mart contract* furnished information in real-time. During the mapping and clustering process, the values used in SVML have a higher chance of restructuring due to a variety of factors, such as choice of goods and supplies, period of usage, storage, and energy consumed, and product costs subjected to existing market value.

Classifiers are used to cluster and model the data based on the critical factors identified above. As per the s*mart contract* (material, finance, stock value, and transport), the interventions are studied, and influential factors are processed separately from the clustered data. During the engineering and modifications, AD modeled is compared with the referenced specifications for uniqueness and data integrity. This helps shareholders leverage IBR and BPR concepts in industrial practices operations (Anand et al., 2021). Data obtained are then correlated with the existing data for rectifying the errors. Then, data from modeling and training are clustered using the K-mean ML method due to its segregation phenomenon, matching the category needs received from internal and external stakeholders. Hyperplanes obtained during the clustering also help correlate the data from each section (Manimuthu et al., 2021b; Manimuthu & Dharshini, 2020). Both positive and negative hyperplanes out of K-mean values are modeled and validated in real-time to avoid any misinterpretation of data from continuous iterations as the design phase involves a smart contract, which is supposed to be agreed upon by all involved.

4.3. Stage 3: Operations

Custom-centric and data-driven decision-making help to identify critical insights about the AD modeling's influential factors. This stage consists of the *design phase* and the *remodeling phase.*
The first phase constitutes raw data where all the factsheets and vendor quoted values are fed into the ML models, and trained values are correlated with the existing data. This phase provides a glimpse of mandatory modifications that should be done during the next phase, *remodeling*. AI value depends on both phases as data emerging from multiple sections such as assembly, fitting, and polishing are gathered. Meanwhile, the data insights and correlation matrix values from SVML and K-mean clustering are studied closely in the remodeling phase. Data with errors are removed, the clusters are re-trained, and the classifiers are revamped. Errors accumulated during

this remodeling are stored in their respected sectional data repository. Policy changes are mutually shared in the event of any cost breakup or energy over-usage. Details of the stakeholders involved are also restructured.

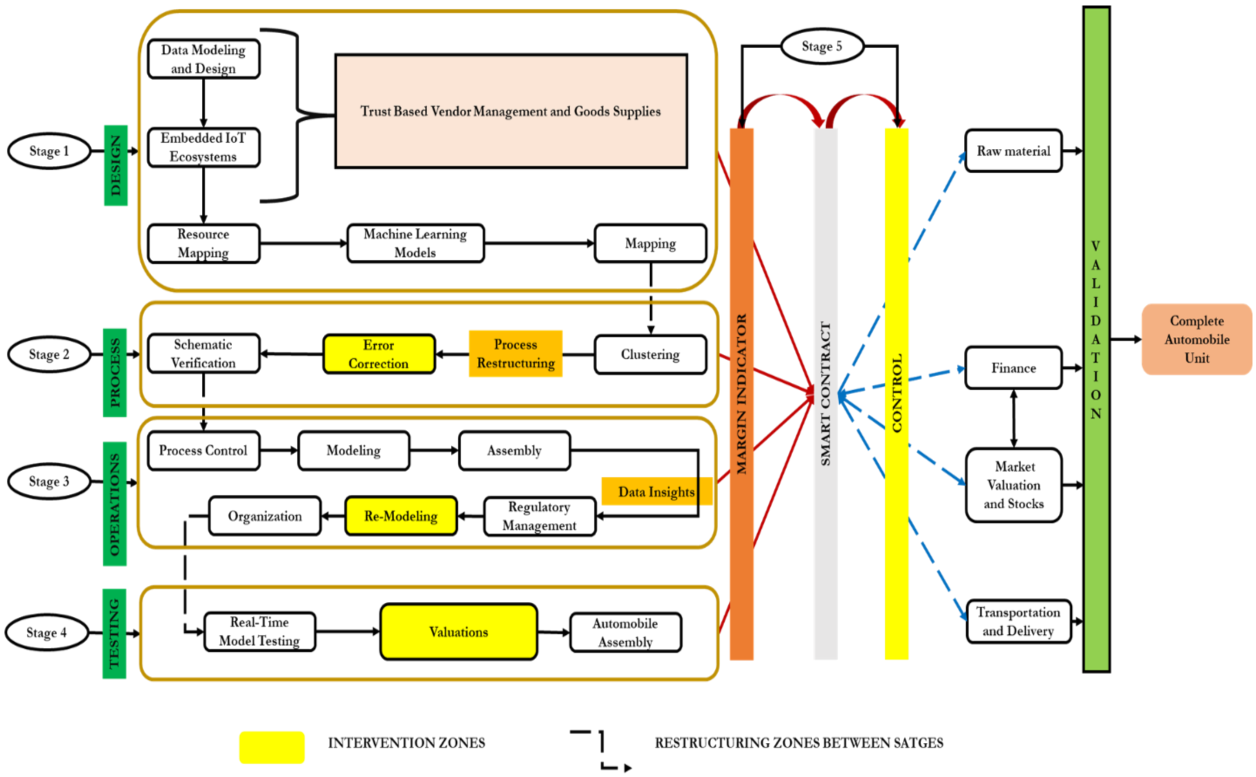


Figure 4. Schematic of the proposed AD modeling.

4.4. Stage 4: Testing

The MI data accumulated in the cost and energy wastages and utilization areas are modeled and shared with the participating agencies. The s*mart contract* for raw material to transportation is effectively handled, and regression values obtained from the training and classification are studied. Data estimation, MI modeling, and real-time model testing will seriously impact the optimal range of MI threshold identified during error correction, remodeling, and data insights, modeled using the IBR procedures (Dolgui et al., 2020).

4.5. Stage 5: Control

Considering the supply chain factors in BPR and IBR during the modeling, testing, and analysis phases of AD, the s*mart contract* and MI values can provide optimal viewpoints for the smooth and safe delivery of supplies with the final product to the commercial market for sales and services. Figure 4 illustrates the operations flow of smart AD processes involving s*mart contracts* and MI designs. Data obtained across the supply chain will be grouped, mapped, and clustered as per their EOQ and s*mart contract* status in real-time. These data are continuously used for training and testing to find the optimal MI value. This AI-based data-driven decision-making is required to improve the overall performance of the smart industrial environment in real-time.

5. Case study and deployment evaluations

The AD model developed is basic and requires real-time deployment and testing. The MI and other innovative ecosystems discussed are implemented in a medium-sized automobile manufacturing enterprise to support and validate the use cases and production improvisation capabilities. However, depending on the characteristics of the case, implementing these features may not be possible without diverting or halting the functions, operations, and other performance-related organizational goals. Many small- and medium-sized automobile manufacturing companies and startups actively participate in the testing, deployment, and valuation of emerging smart technologies in the business and operations. This ensures reasonable returns in terms of performance improvements, productivity enhancement, and robust business modeling in real-time.

5.1 Industry background

Our case is an innovative firm located in Singapore (hereafter referred to as ABC), delivering autonomous vehicles within Singapore and neighboring countries in the Southeast Asian region. As a demographic modification and smart project design initiative, the company planned to test and try its newly renovated operations and logistics facility into a smart industrial compartment. It is one of their futuristic strategies in the name of Vision 2024, within which an entirely AI-operated smart solution is planned to be implemented in their workplace. The facility is equipped with embedded devices to operate in a controlled, structured environment during the initial design stages. In later deployment stages, the AI functional attributes and s*mart contract* models are deployed by skilled employees in storage, transport, logistics, and domestic delivery operations. Considering the criticality of the quality aspects of the final product (i.e., a vehicle), their control surfaces are deliberately forecast for testing and validation purposes in the industry itself. The overall system design requires a specific operational overview and critical insights to expand a similar approach in other related industrial facilities. Hence, two critical operations theories (IBR and BPR) are used in the AD model development.

Table 2 (see Appendix) describes the project goals with the phases involved. Stage 1 details the product movement and IoT-related data collections and interpretations. Stage 2 explains the design data processing and modeling aspects where machine learning models and other IoT-based data analytics and preprocessing are carried out. Stage 3 iterates the same process but with the help of derivative functions from the early stages of design. The importance of intervention research methods and process reengineering features is applied in Stage 4 of design and post-processing and evaluation. Design methods and other AD elements demonstrated are applied with cost and energy scaling with suitable normalization factors. Specifically, the design implements MI as a novel quantitative metric to add more value to their supply chain practice. The benefits can be forecast for enhancing the overall system efficiency, and this helps attain desirable profits, leading to an integrated standalone system withstanding any market crisis or socio-economic problems in real-time. The other key benefits of deploying and testing AI and ML integrated smart contract models in the design and operations management include:

- Dissemination of product related information (value, specification, performance data) across blockchain member stakeholders;
- Remote monitoring of all sections involved in the design;
- Implementation of ML models in data analytics helps to factorize and manage cost and energy values involved in the design, operations, logistics, and other supply chain practices.
- Significant reduction of the cost and energy involved in transporting goods and supplies, and eliminating hidden brokerages;
- The underlying s*mart contract* policies smoothly handle any legal disputes between involved parties; and
- Critical insights about the interventions in design, control, processing and operations, market risk factors, stock prices, and transportation are handled by the standalone operations theories (IBR and BPR) in real-time.

5.2 Proposed business model

Data relevant to the AD and MI are obtained from the participating agents, vendors, suppliers, and stockbrokers in a leading commercial and AV industry. AD developed for IoT-enabled smart industrial workplace assists the design testing and evaluation process, and analytical insights with the help of MI in the ABC company. The model parameters include energy usage and wastages, cost, and product details (delivery, time, price, and license). The final product delivery involves sequential steps and processes that calibrate the use case of multimodal training and assessment details regarding the cost usage, energy consumption, and wastages involved throughout the product delivery. The investigation involves the following key steps:

- Device management and component classification;

- Detailed evaluation of market pricing and the vendor's quotations;
- Transportation and delivery details and pricing for these actions; and
- Blockchain-based policy formation and regulatory norms.

In the current business practice, supply chain and logistics procedures have many significant areas which directly influence the overall industry's productivity and performance. Engaging AI and adopting blockchain helps the industrial system plan restructure and organize the sections towards sustainable process automation and control. The results provide a detailed evaluation of different processing and control procedures that effectively interpret the data generated from embedded components, smart sensors, and IoT devices. Identifiers and classifiers used during the classification help the business model handle the logistics and transportation of vehicles until the retail product is delivered to the consumer market. MI will assist in handling the market valuation and pricing functions, providing detailed insights on every critical aspect of design in real-time.

6. Modeling and design simulation

The data-driven decision-making using ML models in IoT-enabled smart environment involves three major domains: Resource Mapping, Data Analytics (Market Trends, Pricing, and EOQ values), and s*mart contract* (Application Logic Contract [ALC] or Smart Legal Contract [SLC]. They provide an optimal MI value and detailed insights into every contributing factor.

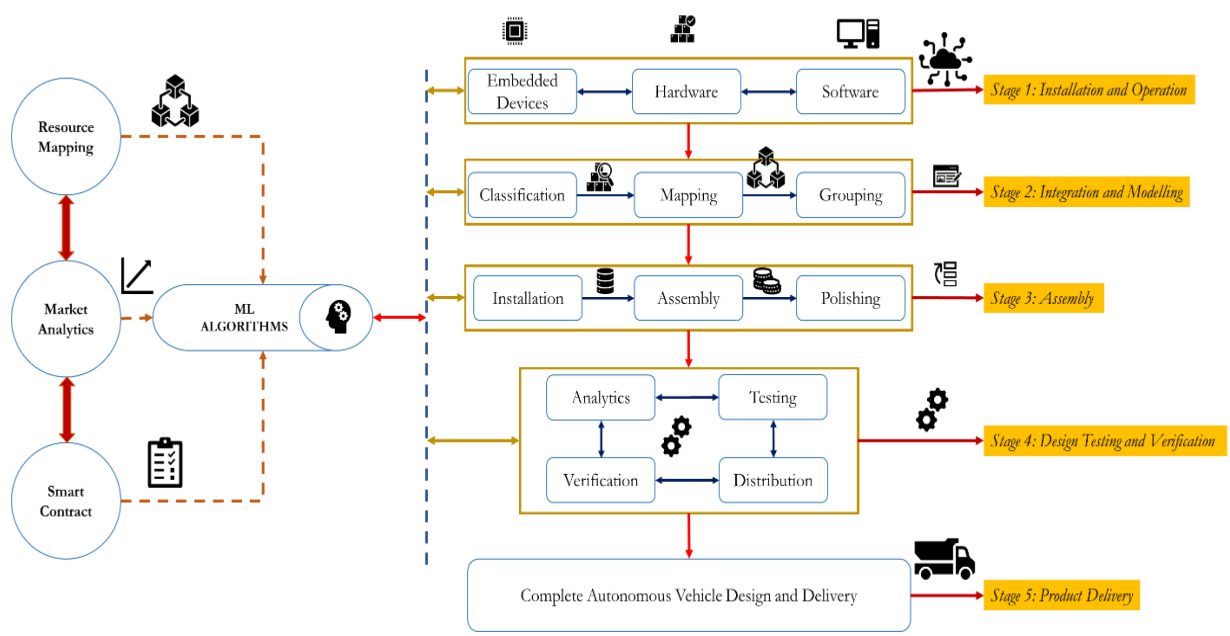


Figure 5. Detailed distributions and stages involved in AD development

As illustrated in Figure 5, these elements deliberately testify to the actions in the industrial environment, from the material ordering and services until the final AV delivery. Testing and evaluating components for reliability and flexibility is carried out by the s*mart contract* and model-based training using SVML and K-mean ML models. Major test results are tabulated to find the use case of MI in the operations and logistics performances.

6.1 Installation and operations

Preliminary experiments are modeled for testing and deployment in this stage. The data generated are collected from different embedded devices and integrated. Data labeling, sampling, collection, and processing occur after installing specific device drivers and firmware once the operations and scheduled processes are initiated in the industrial unit. Inclusion of intervention-based research strategies and process restructuring is done based on these industrial data insights. The energy spent in operations, transport, mechanical drive train, and delivery are critically examined. Similarly, cost functions from every industry section are closely monitored and estimated. Critical findings from this stage include:

- Identification of damages to tools and devices;
- Labeling, scanning, and classification of devices;
- Clustering and mapping of components as per s*mart contract* and agent-based factsheets;
- Specifications check and validation of the license;
- Gross estimation of the storage period, cost, and energy; and
- Market and quoted pricing during final product design and delivery.

6.2 Integration and modeling

After the detailed collection from multiple reliable resources and correlation of data as per contracts and data sheets, the data are processed under three time-controlled critical steps: classification, *mapping*, and *grouping*. Following these steps is mandatory to update the datasets and stored values of component identification details, fact sheets, and vendor listings in real-time. Since the industrial environment is IoT-enabled, data processing has become sophisticated. Nevertheless, the only significant constraint in this multi-sectional derivative functionality is the originality and shared data type checks before processing. All these data are raw and require mandatory preprocessing before being taken to the analytics modules.

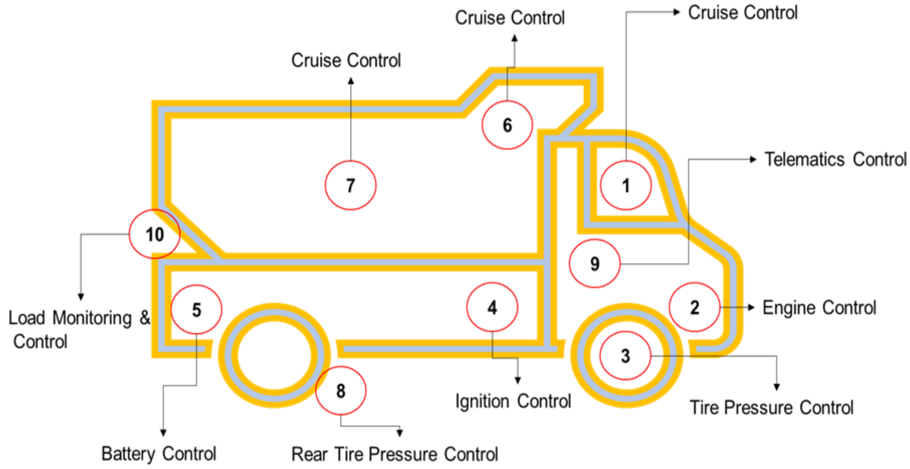


Figure 6: Controls handled by embedded devices in AV (sample model)

Data related to the devices, methods, firmware, and other embedded devices are considered in the ML modeling and MI value findings. Errors accumulated during this stage will be stored and classified according to company standards and industrial methods. In case of any damage or fault during delivery and transportation, factors affecting the originality of data are cross-referenced with authorized suppliers according to their license, period of usage, delivery, storage, and return and replacement policies. Any fault or damages during assembly, fitting, or testing inside AV, the cost and energy involved in the process will be given due attention by its s*mart contract*. Figure 6 shows a sample of embedded devices that need to be tested and deployed inside the vehicle. These devices are tested individually and coordinately to understand their working mechanism and performance. Configuring and modeling as per the current market trend and business methods is quite challenging.

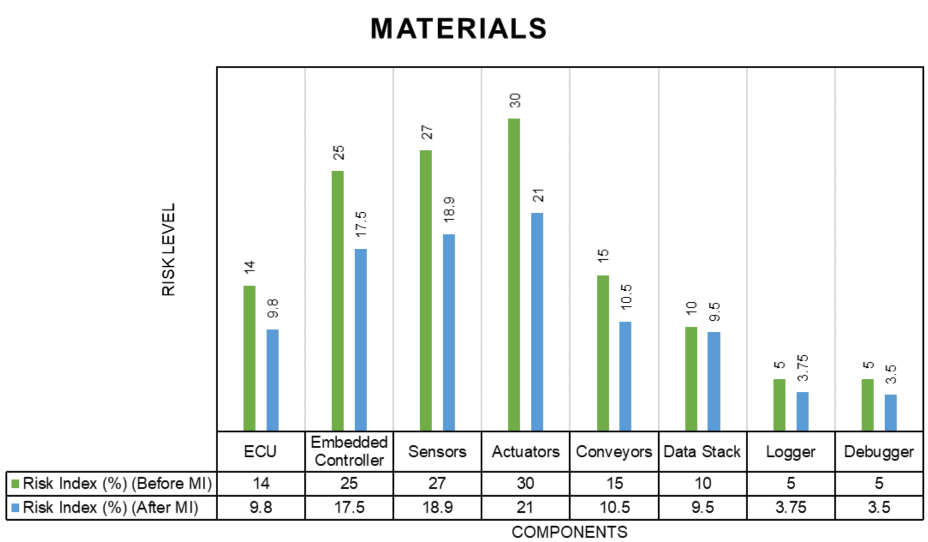
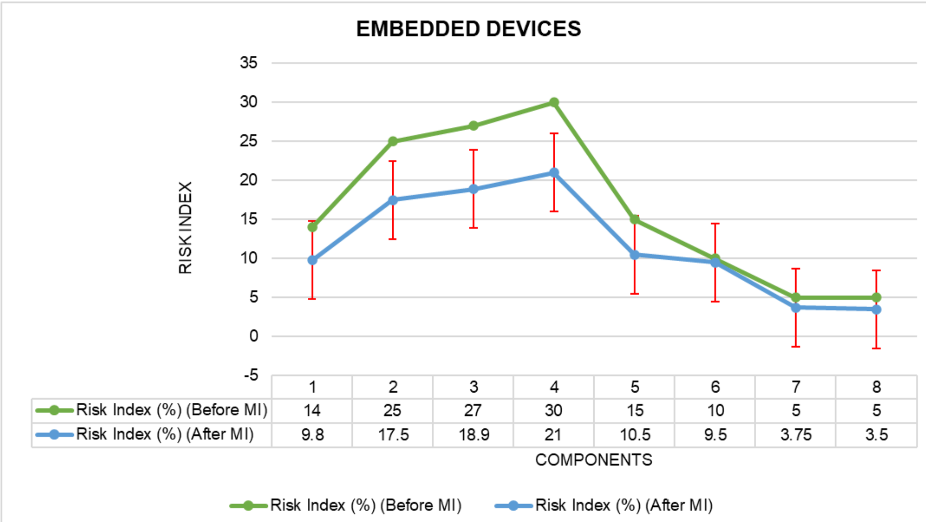


Figure 7: Risk level involved with devices using MI during the redesign

In this modeling stage, MI and *smart contracts* have deliberately improved the risk index in terms of energy and cost (see Figure 7). This leads to redesigning the actual orchestrated activities as per the least energy wastages at optimal cost throughout the operations, delivery, and transportation of the complete vehicle to the consumer market.



	1	2	3	4	5	6	7	8
Risk Index (%) (Before MI)	14	25	27	30	15	10	5	5
Risk Index (%) (After MI)	9.8	17.5	18.9	21	10.5	9.5	3.75	3.5

Figure 8: Risk index calculation using MI (before and after redesign)

Figure 8 depicts basic components involved in the AD modeling that are closely evaluated using the obtained MI values. It is evident from the experimental results that restructuring and intervention-based approach (after implementing MI in the design) cumulatively reduce the risk level by 2-4.5% (as per the components EOQ values and cost margin). This range may go higher on a bigger picture when all the sections involved in industrial operations are modeled. Furthermore, cross-comparisons are made with the existing data from an industrial operation against current AD modeling to add more weight and graphical insights. They show that 0.8-1.3% of risk is reduced due to the MI implementation in the design. As Figure 7 shows, components with indices 6, 7, and 8 have negligible error differences, whereas components 3 and 4 have a high level of critical insights, so redesign actions are deployed. This concludes the effectiveness of MI in reengineering processes involving components required for final AV delivery to the market.

6.3 Assembly

Design setup requires assembly and testing of goods and components. Functional testing on these elements generates datasets with which clusters and vectors are modeled for ML training and validation. Since assembly involves RPA and skilled labor, managing these works is assigned to the *smart contract*. Insurance coverages for fatality or any unusual circumstances are kept ready before the process is initiated in the AD. The stakeholders and vendors will also announce that the devices come with two modes of the *smart contract*. Components 1,2,5,7 come under application logic contracts, whereas 3,4,6,8 are assigned with smart legal contracts as per the industry norms and *smart contract* regulatory amendments (Manimuthu et al., 2021b).

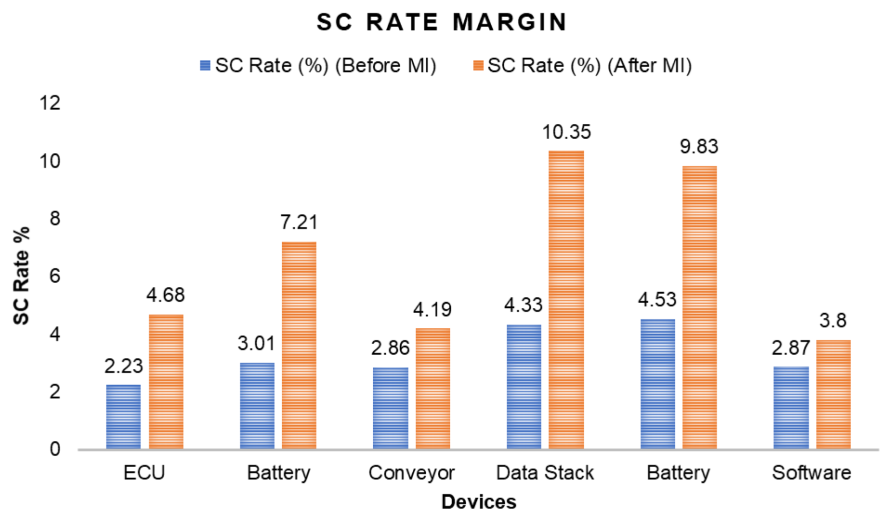


Figure 9: Improved smart contract values using MI in the operations

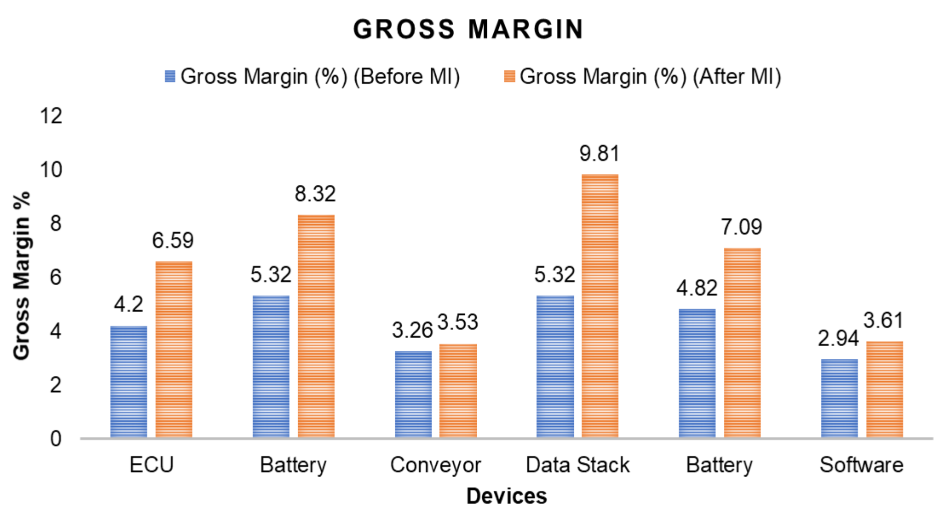


Figure 10: Improved gross-margin range after using MI in the cost estimation

The three underlying steps in the assembly stage are Installation>>Assembly>>Polishing. These steps are managed with variants at different times for smooth operations. During the assembly, insurance and license details are verified. It is also understood from the training results that two significant insurance holdings (i.e., pure holding and intermediate insurance coverages) are deployed in the device purchase and installations. Depending on the type, cost, market value, risk of investment, and local delivery interest range, they are characterized and deployed in the AD modeling. Figure 9 summarizes the experimental details of using MI to improve critical components' gross margin level from ordering and purchasing. Similarly, for the same devices under the same s*mart contract* policies, the gross margin calculated with their MI value is shown in Figure 10.

It is estimated that for every product used in the AV design, about 1.2% to 1.8% of gross margin is achieved using MI in their purchase and procurement. Meanwhile, as per the s*mart contract* rate values, the data obtained shows a significant improvement of 1.65%-2.0% while using s*mart contract* and MI in the design restructuring and modeling process.

6.4 Design and testing

Data analytics and decision-making are the two critical components in this design stage. ML-based values, training datasets, and s*mart contract* instances are developed and modeled using assembly-level data. These datasets help to understand the actual performance of MI in the existing operations and design. Four compilation steps are mandatorily executed in this stage of AD modeling. These steps are non-sequential and cyclic in nature: *Analytics>>Testing>>Distribution>>Verification.*

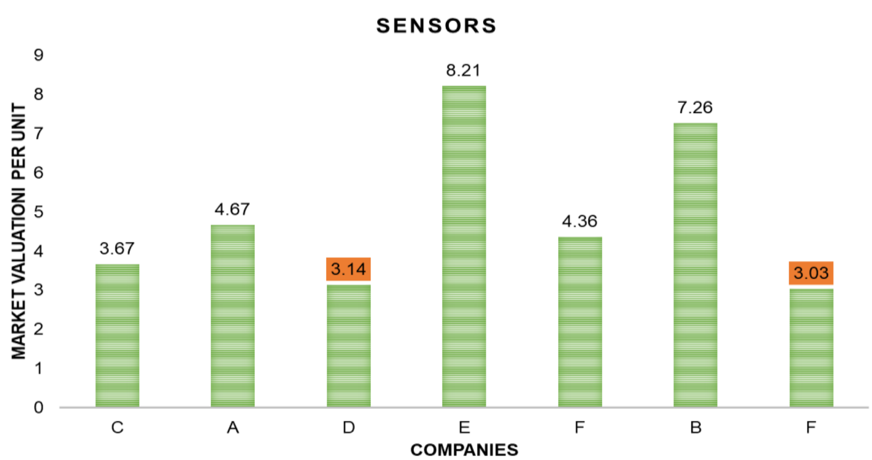


Figure 11: Efficient estimation for purchase as per purchase value among different vendors

The ABC company's share value is estimated according to their market trends and consumer interest during the analytics and evaluation. Almost 15-21 embedded devices are purchased from different suppliers and vendors. As Figure 10 shows, one of the most critical components (sensor) is modeled as per the purchase value from different suppliers. Using MI in design and analytics, the optimal value for the sensor is identified, and the vendor who is ready to supply in and around that value range is selected for s*mart contract* agreements as per industrial regulations. Figure 11 shows that companies D and F have quoted an optimal and accountable rate for sensors per market valuations. Table 3 in the Appendix shows that the agents involved in

AD modeling benefitted from MI in the market value, enterprise value, delivery surcharges, and overhead margins. Thus, adding these performance modifications throughout the industrial operations can improve the energy usage and cost issues in the long run, helping the industry sustain itself in the commercial market without any unconditional losses.

6.5 Product delivery

Product delivery is the final stage of AD, where all the datasets, model values, MI, and s*mart contracts* are actively deployed in the modeling and performance management. As the design undergoes a series of modifications and restructuring, the underlying core objectives are re-evaluated. All the active stakeholders are notified of the changes, and written concerns are regularized for full deployment of services to the delivery section for smart transportation to the commercial market. As in the purchase, for the vehicle delivery and distribution, many potential vendors and brokers are brought into partnership for smooth delivery to the consumer.

The brokerages and hidden margin costs on every product until the delivery are eliminated from this process due to the active deployment of MI and s*mart contracts* in the product delivery chain. Table 4 in the Appendix provides a detailed comparison of dealers' sales margins and the incremental amount of revenue from the deployment of s*mart contract* and MI value in their delivery and transportation of the vehicle to the commercial market. On average, the sales margin is improved by about 17.2-22.5 percent. In a similar perspective, revenue gain from vehicle sales reaches a whooping level of 1.87%-2.24% above its current state of gross revenue. This applies to all the service providers irrespective of market share, company agreements, and type of s*mart contract* involved in the AD process.

This range is optimized as MI accounts for a co-variance level of 0.25%-0.38% in their overall value determination in each design aspect. Figure 12 shows the detailed experimental result of energy wastage reduction during the operations. Some criteria like damages, defects, flaws, and failure of devices during training, testing, fitting, assembly, and delivery are not accounted for in the AD. The predicted MI values are optimal only within the controlled smart IoT-enabled industrial environment. Thus, these operations are subject to the robustness and flexibility of devices and their warranty for industrial usage.

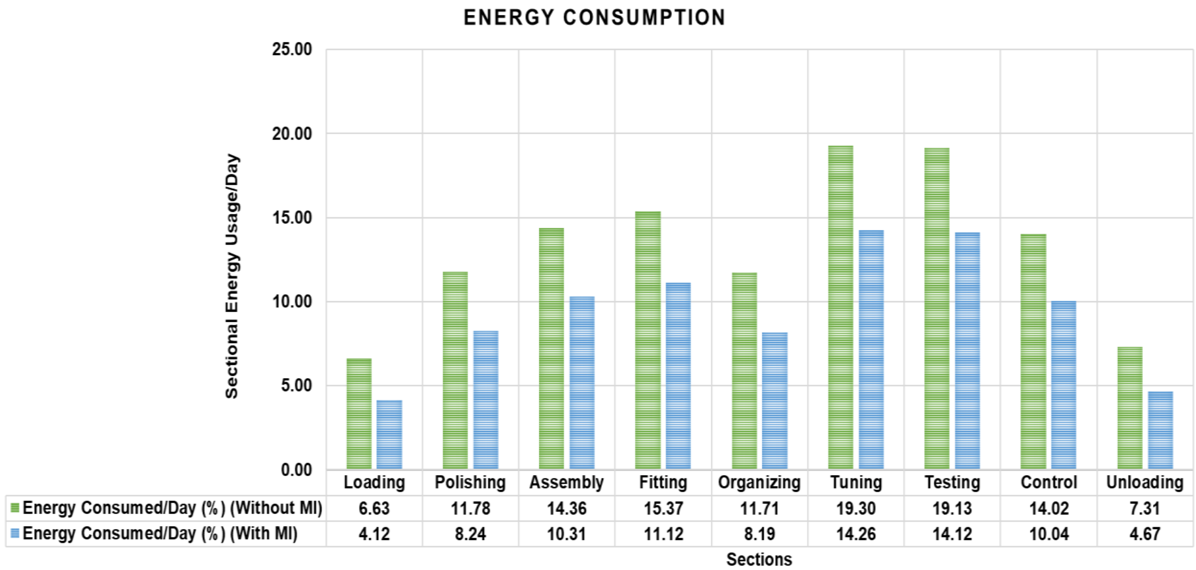


Figure 12: Experimental result on energy wastage reduction across operations

7. Discussion

The experimental AD concentrates on the commercial automobile vehicle design. In a smart IoT-enabled AI-based industrial environment, the developed model is tested intensely for its performance, challenges, practical deployment difficulties, testing methods, and modeling. The present study showcased the effective use case of machine learning models in data analytics, testing, and process redesign. In line with the theoretical findings of the prior studies (Hastig & Sodhi, 2020), this practical study has proved that adding machine learning models to data analytics and decision-making will provide efficient cost and energy management solutions in almost all industry sections. Quantitative and qualitative analysis becomes feasible due to the IoT-enabled sensors and embedded components in the AD. Data collection, modeling, training, and analysis from all sections and stages help to better understand operational behavior and show a viewpoint to withstand a globally competitive commercial market (Adhikari & Bisi, 2020). The supply chains that are enabled with ML models assist the active shareholders of the industry in the acquisition of their initial investments. This becomes practically feasible due to developing and deploying *MI* as a novel usage level indicator in AD modeling.

Our study supports that uncertain market conditions, component unavailability, and environmental adversaries are critical factors affecting the transportation sector. AV design and deployment require sustainable operations, including reliable cost, reasonable energy utility, and intelligent resource utilization in real-time. Our findings suggest that the logistics process should be reviewed if these attributes are not appropriately quantified. Thus, major restructuring needs to be carried out in the AD developed to retain business models, operational methodologies, and supply chain practices. The modeling parameters involve three main components: energy, cost, and policy governance (Nofer et al., 2017). Our study re-engineered these elements for future smart operations, control, transportation, and distribution. The developed AD showcases the effectiveness of MI in revamping the automation processes. Using ML algorithms, resource processing, and predictive analytics help ineffective resource utilization, smart business automation, and supply chain practices in real-time. The study helps to identify the defects, flaws, and errors involved in typical industrial operations. As the regulatory features and policies are regularized using a s*mart contract*, all queries and discussions can be easily handled by their respective sections and teams. Thus, operations can continue without any interventions and redesign in general. The developed AD demonstrated a series of sequential steps that involve moderate redesign and interventions in the existing business methods and industrial practices. In the proposed design scheme, five qualitative decision-making elements were used. These elements are as follows:

1. Reliable dataset from every individual tool and device supplier;
2. Machine learning models for data analytics, processing, training, testing, and evaluation;
3. Existing energy and cost function values;
4. *MI* is used in the process of design revamping; and
5. The s*mart contract* includes industrial policies and regulations.

These elements act as the game-changer in the overall reengineering of the existing methods. Data collected from different operation stages are correlated and modeled for better AD modeling decisions. The s*mart contract* acts as a barrier for the suppliers when there is any defect in their supplied product. As part of the design, energy usage and cost management have been considered. The MI developed will identify the optimum usage level for every tool and device involved in the vehicle delivery. This novel estimation and optimal utility level indicator called MI provides a feasible solution without making significant changes in the business and operations. The solution assures monetary benefits to the agents and investors at all levels of AD in real-time. It is also robust under different market demand conditions, profit margins, brokerages, cost and energy, and gross sales margin conditions. In summary, within 90 days, the new AD approach has shown about 11.58% of profit margin improvement, excluding the gross sales profit in the same commercial market for the ABC company within the Asian market. The profit is assured with certain extended features that offer more insights on data analytics, cost, energy estimations, and redesign process use cases. These include:

- Clustering and classification of component-level data (agents, suppliers, and stocks);

- Logistic methods and operational procedure;
- Market trends and consumer interest;
- Order value vs. delivery returns;
- Sales, services, and stock pricing; return on investment; stock values and percentage gain;
- Gross margin gain for every individual component; and
- Liveliness and consumer interest.

Using MI values, optimal threshold limits for the industrial processes were obtained to satisfy the features with preoperatory functions and principles. This ordeal procedure helped connect, correlate, and evaluate optimal solutions for effective operations restructuring in the ABC company. AD with MI in the industrial procedures assured profitability of around 2.8%-3.4% in the design implementation and experimental phase. Thus, it acts as a selling point for its shares in the markets. Since the implemented AD has used a preprogrammed s*mart contract* for its policy formation, demand-side management has become more flexible and reliable in real-time.

8. Theoretical and Managerial Implications

The present work contributes to the sustainable logistics and AV supply chain literature by focusing on the design, manufacturing, assembly, and transportation processes. Key theoretical implications of the present study are:

- The present study can trigger new intervention-based validation studies in process restructuring and design environments beyond the AV domain (Hedenstierna et al., 2019; Tao et al., 2020) and provide experimental evidence for digital encapsulation in a blockchain-based smart contract environment (Holmström et al., 2019).
- The proposed design method uses IoT-enabled smart devices and embedded components and captures real-time data for design, modeling, analysis, training, and evaluation. Both SVML and K-Mean clustering ML models provided cost estimation, product condition summary, and energy calculations. Thus, the study deliberations advance the research discussions leading to integrating ML models with the design phase and operations, articulating their real-time usage in energy management, cost modeling, and inventory movements. It can also prompt the deliberation for new performance metrics, which can be integrated into sustainable supply chain frameworks.
- The study also triggers research interest and focuses on ranking and assessing the key sustainability risk factors that can easily be customized within the AI-enabled environment across supply chains. It may trigger new theories and business models,

especially in the sustainable logistics domain. For instance, highlighting the role of customizable technology-oriented policies in AV design, the present study sets a new benchmark for advancing modeling and design in the field of sustainable logistics.

In addition, the present research offers several managerial implications that can benefit the supply chain and logistics operations managers.

- This study systematically evaluated the AV logistics and supply chain practices regarding resource utilization, pricing, energy, and market policy using AI and blockchain in real-time. Investors, policymakers, and shareholders may explore underlying procedures with high transparency and visibility over supply chains to assure a desired return on investments. Also, stakeholders may consider redefining their distribution and warehousing policies based on the recommendations received from the AI- and ML-enabled integrated cost and energy monitoring systems (Gružauskas et al., 2018).
- Compared to the current AV development practices, the proposed MI helps to reduce ambiguity, uncertainty, and complexity of operations, while assessing energy and market conditions (Niu et al., 2022). This leads to sustainable socio-economic balance with reliable business practices by minimizing the trade-off risks between different factors (e.g., cost and energy). This would help supply chain managers to make more robust energy and cost-based sourcing and logistics decisions, enabling them to mitigate supply chain sustainability risks (Cao & Shen, 2022) and achieve logistics efficiency in sustainable environments.
- The study deliberations help to reduce the influence of third parties and provide a better control of the supply chain processes, ensuring real-time data sharing among stakeholders. This transformation helps managers to control the AI/blockchain-enabled production environments by integrating real-time stock prices and brokerage. Hence, industrial automation policies and regulatory guidelines inform the design of either application logic contracts (work by validating the communication between devices through blockchain) or smart legal contracts (with the legal remedy in case stakeholders do not fulfill their obligations), which may consider transport mode and warranty clauses.
- The proposed transformation model will support the operations managers in keeping track of all activities within the firm and with less impact on external eventualities. Procurement officers can better control the critical factors, such as lead time, delivery, cost, and inventory duration, to better align their decisions based on the decision of other players across the supply chain. Floor managers in the assembly process can use the SVML and K-Mean

clustering models to improve their cost estimation, product condition summary, and energy calculations. Such integration articulates the real-time usage in energy management for inventory movements. Hence, energy management can be integrated into sustainable supply chain frameworks for cost savings. It can be noted that detailed decision-centric operational procedures provide guidelines to the managers in forecasting the needs and requirements for smart operations with controlled energy wastages and cost utilization in real-time.

- Finally, our experimental findings and novel AD would help the part manufacturer to chart action plans of productions, transportation, distribution, or any sort of omnichannel activities in advance without bias in the working conditions. The findings of this design articulate the urgent need for applying smart technologies which help the industry, including reverse logistics and wastage scrapping procedures, by making the process leaner and greener. With these extended scopes, unbounded controlled decisions and qualitative managerial flexibility can be achieved in all aspects of supply chain and logistics procedures in real-time.

9. Conclusion

There is a growing need for developing sustainable logistics systems in the modern world. With the growth of autonomous vehicles and the alternate energy source, the domain is topical for integrating advanced technologies, such as AI and ML techniques, in design and manufacturing operations (Van Brummelen, 2019). Such integration enables product tracing and ensures system efficiency, maintenance, and secure operations (Hasan et al., 2020). While doing so, it is important to protect the data from the potential safety risks and to be robust in tracking possible factors that directly impact the businesses. Such practices facilitate efficient data management, processes, and control in the automotive domain.

The model provides a detailed framework for deploying and testing smart techniques for vehicle assembly, process automation, design methods, and data-driven decision-making within the boundary of s*mart contract* standards. Additionally, it helps the operators and investors to self-check their operating procedures, industrial operations, and processes involved in the AV supply chains, focusing on cost and energy in real-time. This is a critical asset for the smart automated industry because any defects/damages in the tools and supplies can be immediately identified and rectified, and suppliers are instantly notified with their unique identifiers. The study contributes a novel value indicator, *MI*, to AI-enabled smart contract environments, where the orders are processed, and AD operations can be executed. This provides a new perspective on inventory planning and overall supply chain strategy. Modeling comprises sophisticated techniques, such as data normalization, clustering, tuning, and vector calculations that can be executed sequentially for cost estimation and energy evaluation. The study uses explicitly SVML model with a clustering approach that would train, test, and evaluate the data and log them for future reference, with less impact on market trends. This highlights the market pricing and costs involved in the design. Thus, MI helps the operators visualize, fix, modify, replace, and finalize the procedures and processes concerning market influence and demand-supply trends. The entire process is prompted by two operations management theories, IBR and BPR, to provide managerial insights and redesign ideas.

Our study suggests that a customizable AD, along with MI predictions, can be deployed in the business operations in any smart industrial sector, including logistics and supply chain, with minor modifications in their existing practices for better productivity, process improvisation, efficient energy, and cost management. Investors, policymakers, and shareholders can understand underlying procedures with high transparency and visibility over the companies' supply chains with an assured return on investments and monetary benefits. The concurrent application of blockchain and AI will assist the logistics operations managers and other stakeholders in making better decisions, powered by automated tools and procedures. Such tools can aid supply chain planners to achieve better outcomes with more visibility for supply chain activities, making them more sustainable and robust.

Like any experimental study, our research has some limitations and offers future research avenues. *First*, the present study has a minimalistic pattern engaging two specific AV industry segments (i.e., AD & smart contracts). Testing, evaluation, analysis, and experimentations executed are limited to AD. The model does not reflect the entire industry's estimate. Hence, the study sets a direction for a comprehensive statistical analysis across a single firm and, subsequently, cross-industry studies among firms and industry sectors in future work. So, we suggest that future studies can be conducted to test and validate the design and modeling approach we proposed in this paper. *Second*, the design and experimental modeling that are solely driven by smart embedded devices are subject to *error*, as their accuracy is highly dependent on the device brand. Also, the MI values obtained will not be error-free as they are subject to market trends, consumer interest, and demand levels. Errors in the stored and processed data may impact the process performance on a large scale. These errors may impact the validity and robustness of data, which is considered as a core element of design function and is the basis of model training, rigorous testing, and validations. These limitations call for novel proposals for future studies aiming to tackle the frequent error incidences. *Third*, the cost and energy involved in the powering up and booting devices may vary. Although the AD deployment design may not take much time, training and testing may become lengthy when using SVML and K-mean ML models. They can be explored through deep learning algorithms (Yu et al., 2019). All these limitations offer scope for future research agenda to sustain the supply chain performance.

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Appendix

Table 1. Studies related to Blockchain & AI in supply chain practices

Reference	Problem Studied	Nature of Study	Approach
Martins et al. (2022)	Buyer-supplier relationship	Unbalanced Buyer - supplier relations	Reputation system
Raj et al. (2022)	Decentralized marketplace (DM)	Tracing procurement issues in 3PL	Digital supply chain
Omar et al. (2022)	Supply chain Cybersecurity	Information sharing among stakeholders	Ethereum
Manupati et al. (2022)	Supply chain Robustness	Managing Supply chain network disruption	Genetic algorithm
Woerner et al. (2022)	Inventory management	Handling penalties in the supply chain transaction	Smart factory - IoT
Grida & Mostafa (2022)	Global Supply chain	Understanding the role of the smart contract in the supply chain	Smart factory - IoT
Boubeta-Puig et al. (2021)	Complex event processing	Modelling Complex Event Processing (CEP) in supply chain	Graphical modelling tool
Liu et al. (2021)	Drug supply chain	Synergising IoT & Blockchain for tracing issues	Smart factory - IoT
Chen & Liu (2021)	Multiple sourcing	Role of a Contract manufacturer in OEM	Ethereum
Agrawal et al. (2021)	Fast Fashion supply chain	Traceability in the production process for quality assurance	Ethereum
Menon & Jain (2021)	Agri-food	Exploring the attributes of Blockchain	Ethereum
Qin et al. (2021)	Industry 4.0	Developing an intelligent smart contract	Ethereum
Gourisetti et al. (2020)	Blockchain applicability	Blockchain applicability framework for food supply chain	Ethereum
Epiphaniou et al. (2020)	Smart contracts	Bespoke blockchain for supply chain traceability	Hyperledger
Lohmer et al. (2020)	Capacity sharing	Agent-based study for supply chain resilience	Simulation study
Wamba & Queiroz (2020)	Decentralized system	Proposing the areas of blockchain in supply chain practices	Digital supply chain
Dolgui et al. (2020)	Cyber-physical supply chain	Scheduling production process using blockchain	Smart factory - IoT

Ma et al. (2020)	Cold supply chain	Digitalizing the multi-echelon supply chain	Digital supply chain
Wang et al. (2020a)	The dynamic information sharing mechanism	Developing sharing mechanism using smart contracts	Smart factory - IoT
Casino et al. (2021)	Track & Tracing System	Creating an architecture for decentralized supply chain process	Smart-contract
Hasan et al. (2019)	Shipping	Developing a distributed ledger for global shipping & trading	Ethereum
Saberi et al. (2019)	Global Supply chain	Applying smart contracts for supply chain processes	Blockchains

A.1 Estimation and modeling

Each piece of equipment and tool involved in the design, transportation, and delivery requires initial investment and close monitoring for effective split-ups between multiple agencies.

The proposed model includes the following notations used for modeling various critical parameters essential for MI value estimation in AD modeling.

A.1.1 For cost evaluation

W = Warehouse point for loading, unloading and delivery

S = Section in Industry

B = Brokerage charges

T = Transportation cost

i = Index of evaluation

O = Order value

k = Lot index

t = Time

L = Loading cost

l = Unloading cost

V = Input iteration for goods and commodities

X = Choice of goods

H = Holding cost

R = Capacity of delivery in w

e = Error function during product usage and delivery

C(W) = cost from raw material to final product

B = EOQ

Θ = Cost margin for products movements

ϒ = Margin/ product

The cost calculation involves all sections of the industry. Equation 1 shows the estimation for every section with respect to time.

$$C(W)= \frac{1}{2S} [\ M+ N]_t \quad \text{where } t \in 1,2,3,4,\ldots.. \tag{1}$$

The estimated cost function for all goods and commodities can be obtained from Equation 1 with their iterations as shown in Equations 2 to 4, where brokerage charges are explicitly included as input out of the same order value.

$$M =\sum_{i=1}^{r}(X_{\theta(i)}\ (V^{(i)}- \beta^{(i)})) \tag{2}$$

$$N=\sum_{i=1}^{r}[B\ (v)^{(i)} + O(v)^{(i)}] \tag{3}$$

$$\beta^{(i)}= \sqrt{\frac{2*O*D}{H}} \tag{4}$$

where the EOQ value varies on a routine basis due to the market value, units of order, and the number of units on hold. They also rely on the type of s*mart contract* and license period.

$$B(v)^{(i)}= 1/2S\ \sum_{i=1}^{n}[\ (\ L_{(i)} + l_{(i)}\ ) *\ T_{(i)}\ ] + \Delta\ e_{(i)} \text{ where } i \in 1,2,3,4\ldots. \tag{5}$$

$$\Delta\ e = \int_0^t \frac{[\ (\ L-r)^2 * T\ (i)]}{O(v)} \tag{6}$$

Estimating the hidden brokerages must be accompanied by error values from every iteration, as shown in Equations 5 and 6. These values must be eliminated or nullified from the design to reach a transparent estimation which is nearly impossible in current industry practices.

The brokerage charges vary with regard to the vendors, suppliers, and transportation time and delivery ranges. This involves a certain level of uncertainty leading to the error margin and is estimated using Equations 7 and 8, where input iterations, associated section, and convergence functions are added. The convergence function helps identify the optimal error correction value to limit the error from subsequent iterations during ML training.

$$\Theta_{(i)=}\ \Theta_j\ - \Upsilon\ \frac{\partial}{\partial j}\ S\ (\Theta_0 , \Theta_1)_{\ t} \tag{7}$$

$$\Theta(v)^{(i)} = \Upsilon \int_0^t S(k_0 , k_i) * V\ (x)_{\theta i} + \Delta\ e(i) \text{ where } i \in 1,2,3,4\ldots \tag{8}$$

$$MI(W) = \frac{\partial}{\partial s} [\ \frac{\Delta\theta(i) - \Delta\ e(i)}{\Delta B(V)^{(i)}}\ ] \text{ where } i \in 1,2,\ 3,\ \&\ \Delta = \text{convergence function} \tag{9}$$

Equation 9 helps estimate the overall *MI* for allowable cost per unit of order needed for purchase or procurement on a temporary basis.

$$\Delta\theta_{(i)}= \sum_{i=1}^{r}[\ X_r(V) * \beta(i)]\ /\gamma(x_r(V)) \tag{10}$$

Equation 10 computes the margin cost function concerning the obtained EOQ values and their respective cost margins. This contributes to the iterative error value modeling Equation 11, through which EOQ errors and cost margin kept on the top of every tool and product are modeled.

$$\Delta e_{(i)} = \frac{\theta i}{\beta i} = \frac{1-\theta_i}{\theta_i^{(r)}} + \frac{1-\beta_i}{\beta_i^{(r)}} \quad (11)$$

A.1.2 Energy estimation

In order to find the amount of energy consumed or wasted during the process, it is necessary to include the cost associated with the transportation. Nevertheless, energy is estimated initially and added with other delivery and transportation estimations for the modeling purpose.

Q = Quantity used

i = Index of evaluation

y = Distribution between sections

v = Transportation cycle

k_c = Energy consumed

k_w = Energy wasted

e = Error function during product delivery + usage

t = utility time

$$E(W) = \int_{i=0}^{r} vy + \Delta K_c + \Delta K_w \quad (12)$$

The overall energy estimation function is shown in Equation 12:

$$\Delta K_C = \sum_{i=0}^{r} Q * \frac{k0 + k1 + \cdots\ldots + kn}{\Delta t} \quad (13)$$

As the consumption and wastages involved distribution and transportation between sections, the transportation cycle and order of quantities are added to Equations 12-14.

$$\Delta t = \int_{i=0}^{r} 1 - \frac{vy}{y_{(i)}} \quad (14)$$

$$\Delta k_w = \sum_{i=0}^{r} Q * \frac{\Delta K_c}{y(i)} + \Delta e \quad (15)$$

To estimate the *MI* value, both the utlity time function Equation 15 and estimates obtained from Equation 12 are added together. To sum up the overall functions, error values are directly added to *MI* as in Equation 16. This sums up the weights with respect to individual quantities in the industry.

$$MI(W) = \int_{0}^{t} \Delta E(W) - \Delta e \text{ where } \Delta E(W) \neq 01 \quad (16)$$

A.1.3 Transportation and delivery

T_i = Transport vendor index

L = loading cost

l = unloading cost

D = delivery rate

R = rate of delivery of goods

e = error function during product delivery + usage

O = order value

T_c = Total cost for transport

$$T(W) = \sum_{i=0}^{t} R * [(\frac{L+e}{O}) / \frac{l+e}{O}] + D \tag{17}$$

Warehouse point of transport to the delivery with their weights and functions can be modelled using equation (17).

$$R = \int_{o}^{r} [(\frac{L+e}{O}) / \frac{l+e}{O}] + \int_{i=1}^{r} T_i [\frac{D+e}{Tc}] \text{ where } D \neq 0 , R \neq 0 \tag{18}$$

As the transportation involves both loading and unloading charges, each of its allied components is added to the modeling equation as shown in Equation (18).

$$T_c = \sum_{i=1}^{r} [O + e + \Delta L + \Delta l + \Delta D]_I \tag{19}$$

To estimate the total cost Equation (19), margin values from loading, unloading, and order values are added together with the error function, which is an integral part of *MI* estimation.

$$MI (W) = \int_{0}^{r} [\Delta T(W) - \Delta T_c] + \Delta R \text{ where } \Delta R = \frac{1-R(i)}{R} * e \tag{20}$$

The overall MI for transport is obtained from Equation (20), which includes a separate entity called R, the rate of delivery of goods that remains static for every product and cannot be changed at any level during its transportation.

Table 2: Project summary

<table>
<tr><td colspan="3" rowspan="2">Business Model:
Experimental modeling, testing, and deployment of energy and cost data out of all sections and services from the industry using IoT-enabled smart infrastructure. Fully automated embedded devices and robotic platforms are deployed in various design, testing, and analytics. Model development is done using the R scripting tool, and interpretations are made using Tableau. Automotive simulation software determines and estimates the margin indicator values for effective cost and energy management. In real-time, smart contracts and allied policies keenly take market values, including economic order quantity estimations. Risks involved in the design, estimations, and analytics are closely monitored by AI-driven data modeling, and smart decisions are made with their respective MI functions.</td><td colspan="3">Problem Identified:
Excessive usage of cost and unprecedented energy wastage are identified in every aspect of industrial design. AD provides smart innovative solutions based on AI-enabled modeling and ML-based data-driven analytics in real-time. This boosts the industry’s performance in all areas, including collections, analytics, testing, design, valuations, and testing. Transportation cost and delivery margins are also considered during the design phase.</td></tr>
<tr><td colspan="3">Team:
Smart IoT-enabled industry requires 10-15 skilled laborers with prior experience in data handling, analytics, and design. Testing knowledge about the robotic platforms, software, and firmware, and additional skill set includes developing and deploying machine learning models and R studio.</td></tr>
<tr><td colspan="2" rowspan="3">Design Goal
Design, experiment, implementation, and deployment of vehicle design model called AD with the help of AI-enabled IoT-based smart ecosystem. They test the randomness involved in operations, logistics, and supply chains. Introducing the novel value or threshold indicator, Margin Indicator, in the design to improve and manage energy and cost throughout the entire industrial operation, thereby boosting its performance in real-time.</td><td colspan="2">Risks and Issues
Data management and analytics due to many embedded devices and sensors</td><td colspan="2" rowspan="2">Dependencies
• Vendors, suppliers, and investors are given weekly updates
• Transparent data analytics and evaluation criteria
• Explicit cost and energy analytics</td></tr>
<tr><td colspan="2">Equipment and Tools:
Sensors, Actuators, Device drivers
Software
Automotive design suits and Software like MATLAB, R studio, and Tableau</td></tr>
<tr><td colspan="2">Project Duration
05-06-2020 to 08-05-2021</td><td colspan="2">Investments
Cost of Project: S$50,000 (including purchase overheads.)</td></tr>
</table>

Table 3: Impact of MI on enterprise valuation (estimated vs. improved delivery charges/rate)

Dealer ID	Delivery Charges (%) (Before MI)	Delivery Rate (Before MI)	Market Valuation (%)	Enterprise Rate (%)	Delivery Charges (%) (After MI)	Delivery Rate (After MI)
ISG021	10.97	21.67	129.46	164.35	5.03	18.13
ISG022	14.97	13.74	93.82	118.62	-16.87	10.20
ISG023	16.04	12.21	87.21	110.15	-21.83	8.66
ISG024	12.97	17.08	108.51	137.47	-6.86	13.54
ISG025	7.95	18.12	108.69	137.71	7.25	14.58
ISG026	9.78	19.23	116.08	147.19	4.35	15.69
ISG027	17.97	17.96	117.89	149.51	-18.05	14.41
ISG028	8.99	17.14	104.81	132.73	3.18	13.59
ISG029	9.60	20.17	120.59	152.98	6.19	16.63
ISG030	8.05	16.21	99.22	125.56	4.12	12.66

Note: Negative Values indicate that Gross Margin exceeds the required limit per the Optimal MI range.

Table 4: Comparisons of margin and gross revenue change

Dealer ID	Sales (Margin %) (Before MI)	Revenue (%) (Before MI)	Sales (Margin %) (After MI)	Revenue (%) (After MI)
ISG021	12.98	5.52	17.2	7.56
ISG022	10.82	11.22	15.04	13.25
ISG023	10.49	14.98	14.7	17.02
ISG024	11.64	3.73	15.86	5.76
ISG025	10.65	6.52	14.87	8.56
ISG026	11.63	3.76	15.85	5.8
ISG027	13.42	14.01	17.63	16.04
ISG028	10.54	1.58	14.75	3.62
ISG029	11.97	6.2	16.19	8.23
ISG030	9.89	2.25	14.1	4.29


DESIGNS
PROCESSES
OPERATIONS
CONTROLS
TESTING
1
2
3
4
5
VALIDATION
Intervention Based Research Insights between Different stages of Operations

fig 2

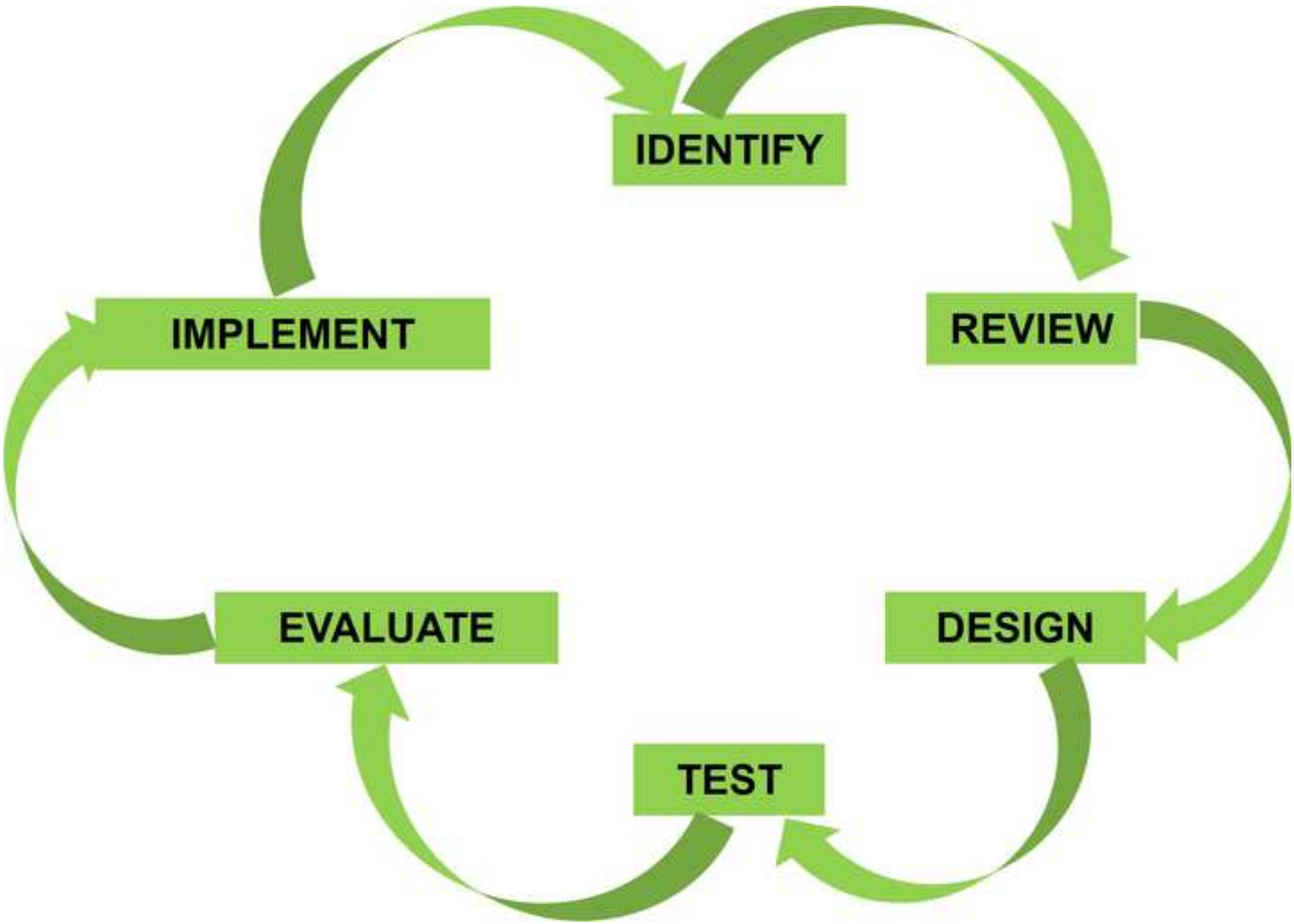

fig 3

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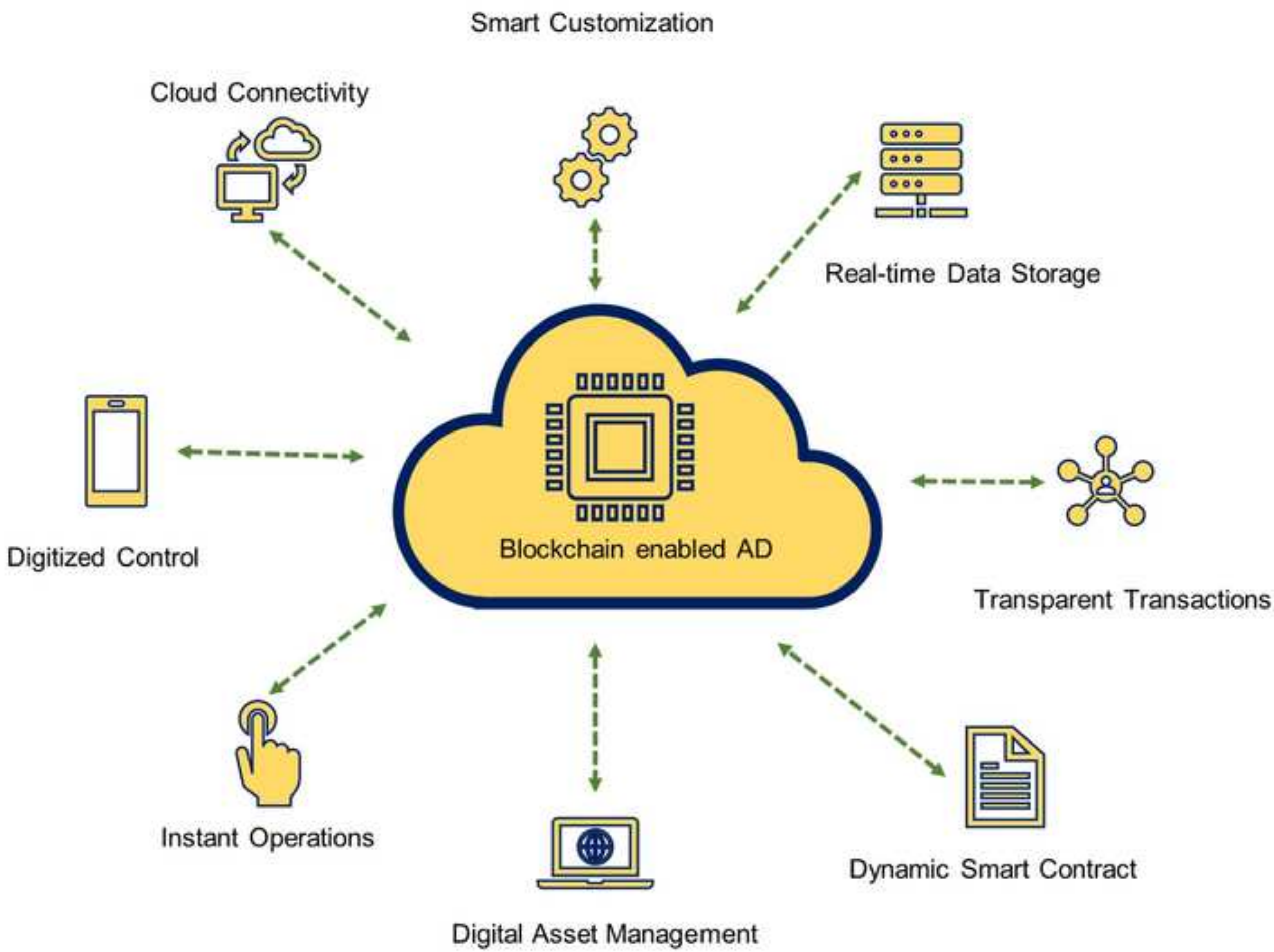

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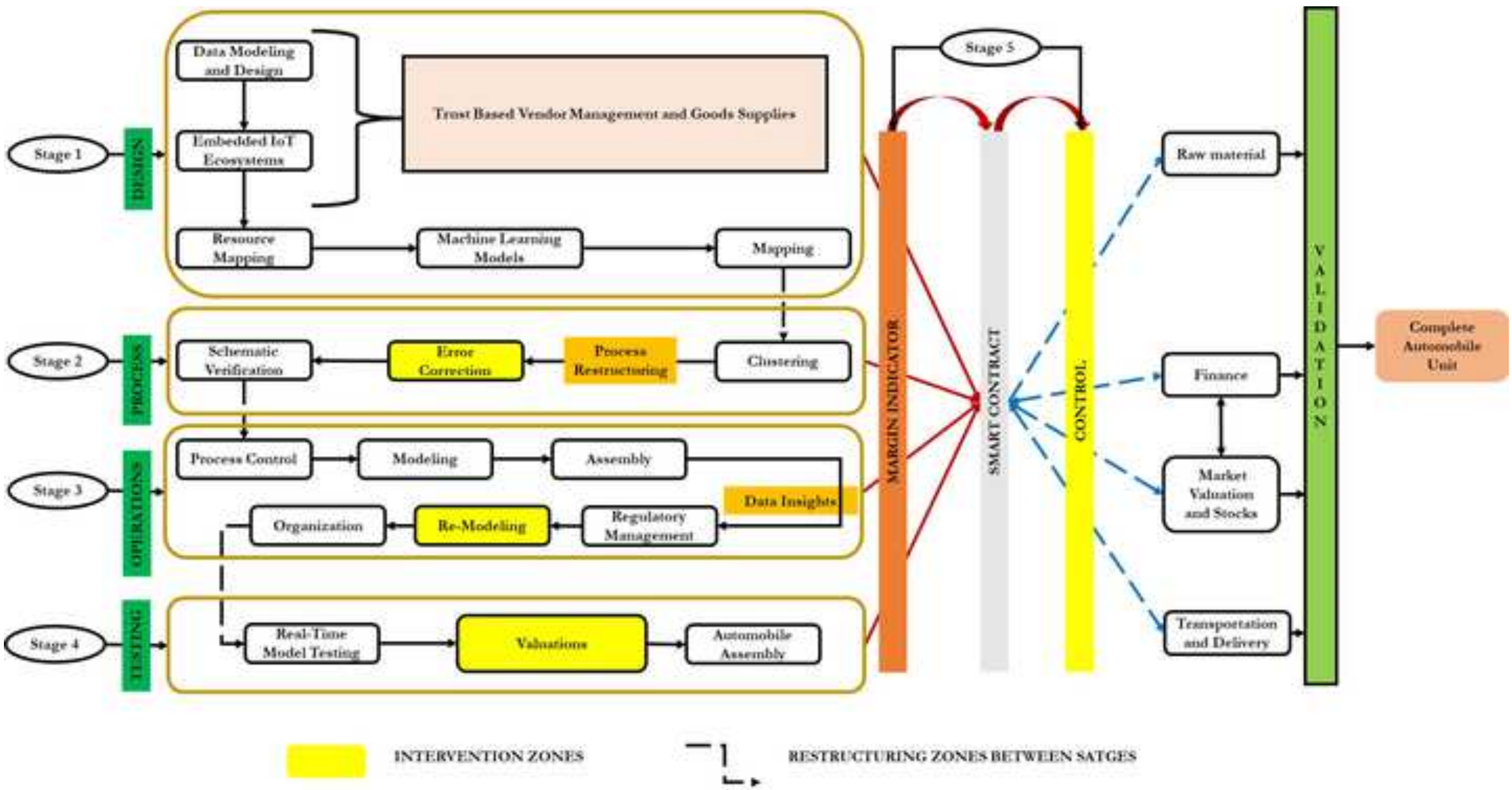
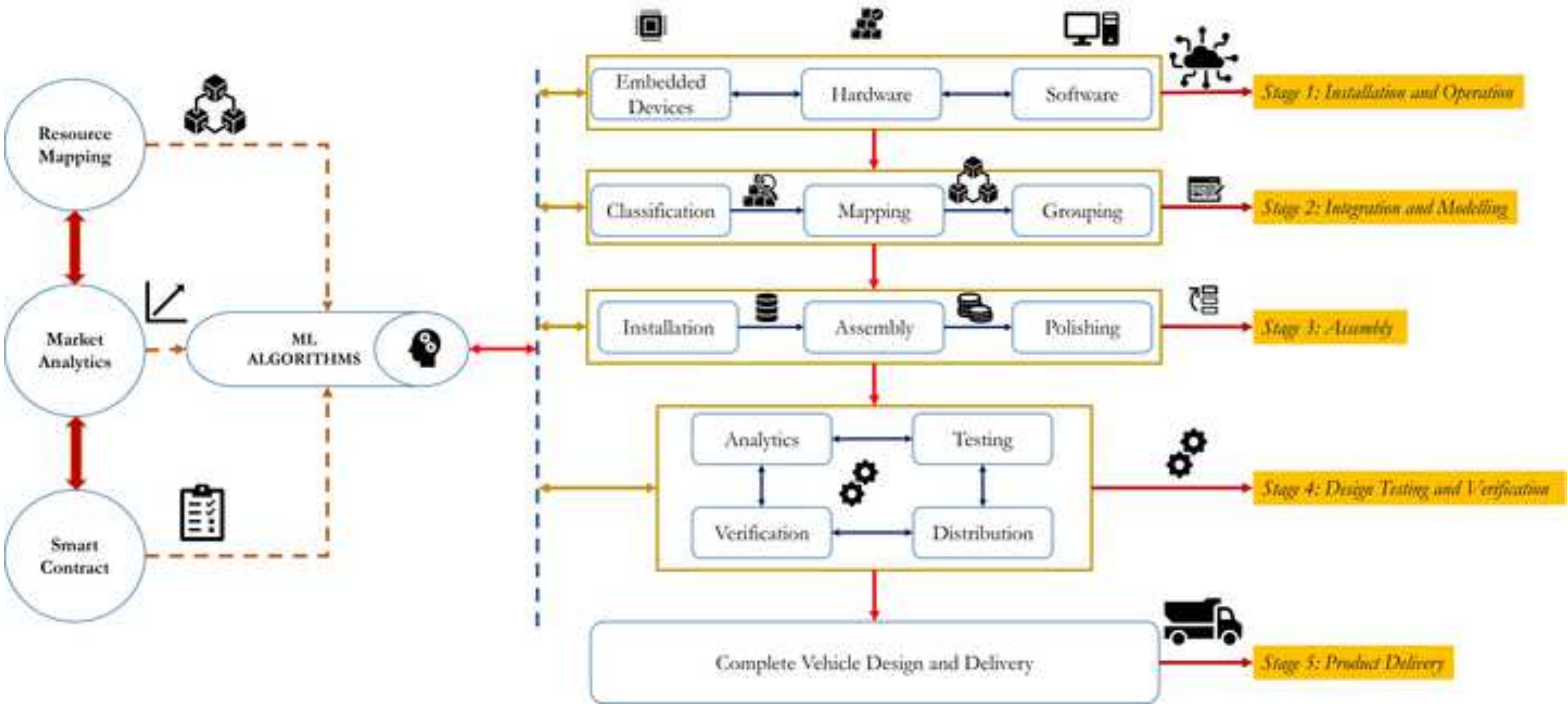
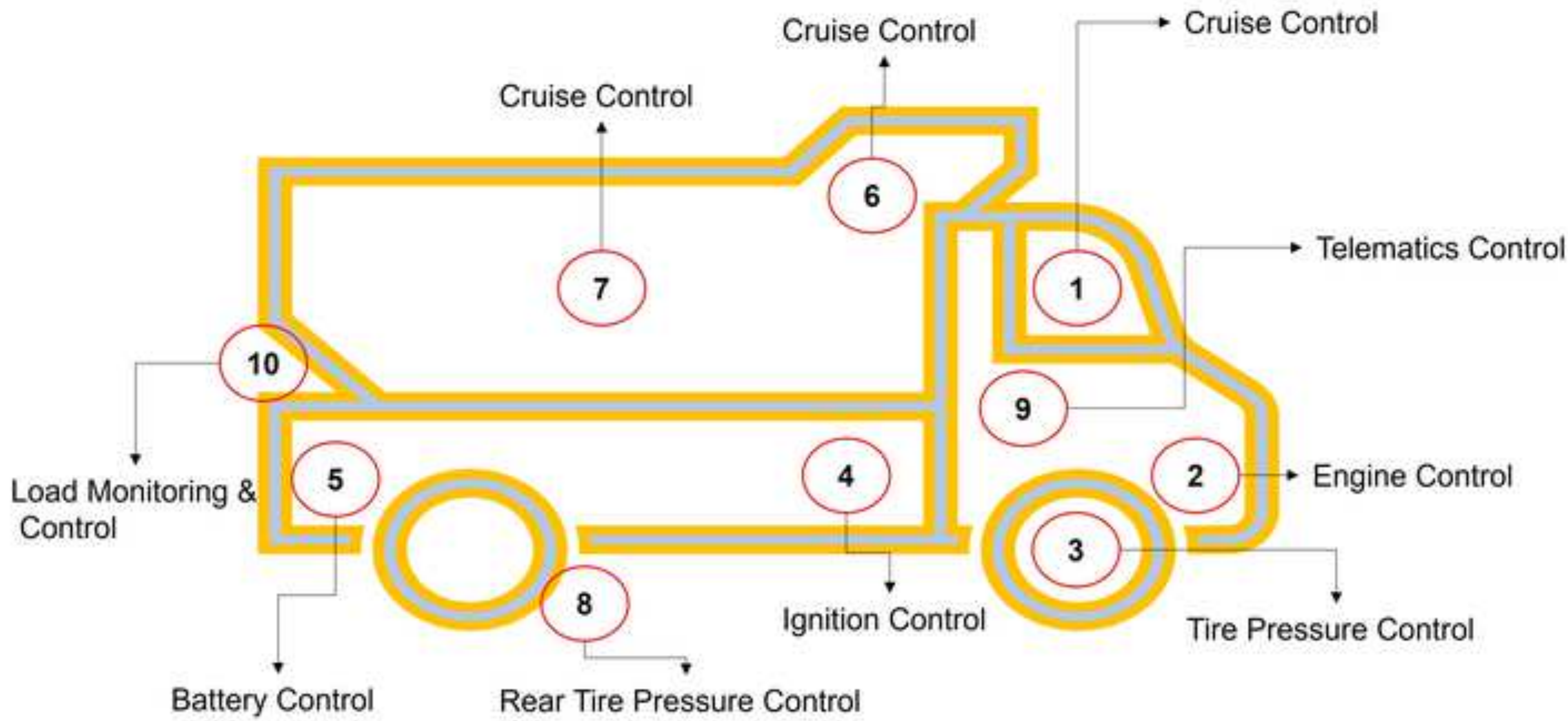


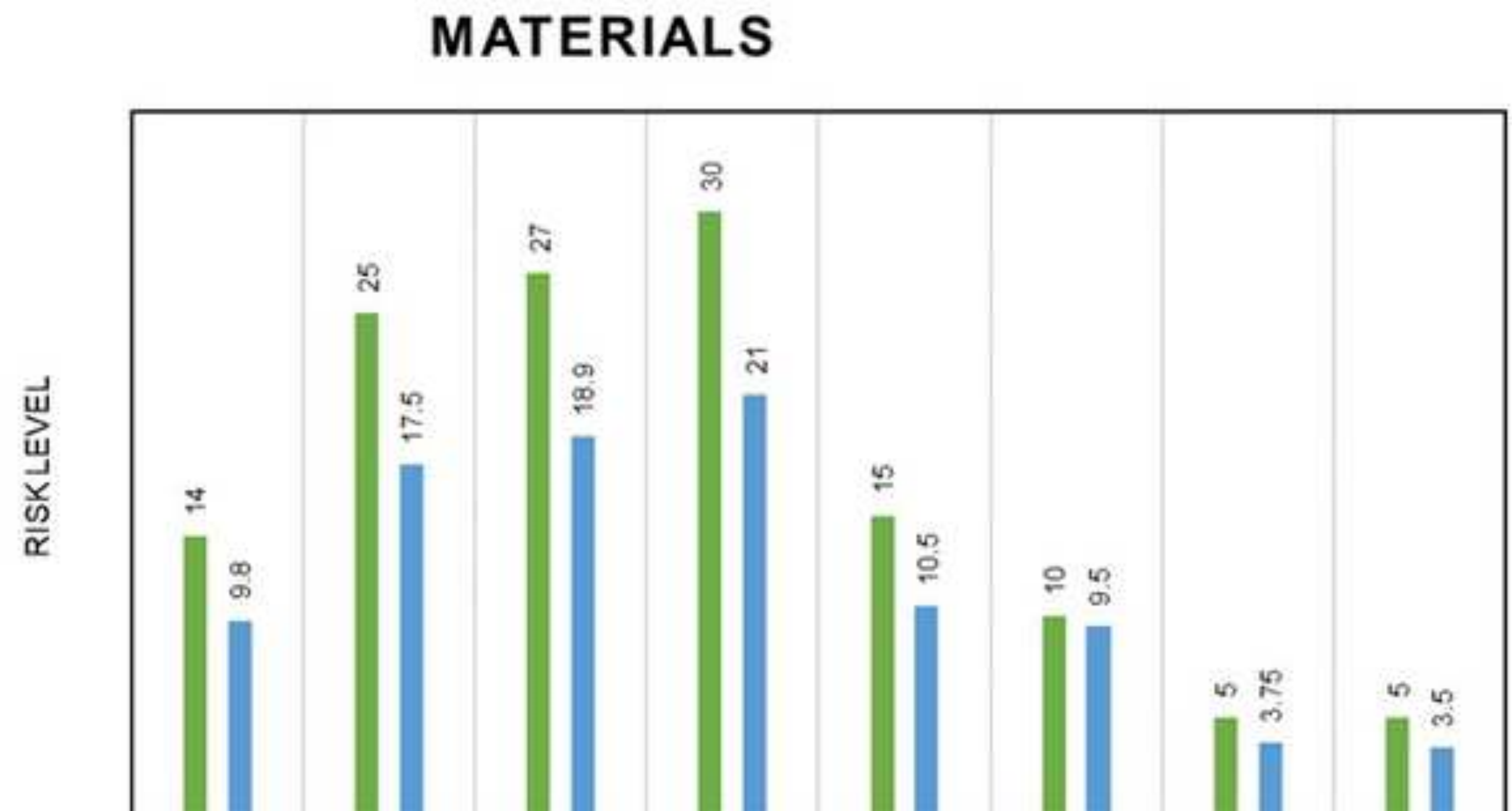
fig 5



Resource Mapping
Market Analytics
Smart Contract
ML ALGORITHMS
Embedded Devices
Hardware
Software
Stage 1: Installation and Operation
Classification
Mapping
Grouping
Stage 2: Integration and Modelling
Installation
Assembly
Polishing
Stage 3: Assembly
Analytics
Testing
Verification
Distribution
Stage 4: Design Testing and Verification
Complete Vehicle Design and Delivery
Stage 5: Product Delivery

fig 6 Click here to access/download;Figure;Fig 6.jpg





	ECU	Embedded Controller	Sensors	Actuators	Conveyors	Data Stack	Logger	Debugger
Risk Index (%) (Before MI)	14	25	27	30	15	10	5	5
Risk Index (%) (After MI)	9.8	17.5	18.9	21	10.5	9.5	3.75	3.5

COMPONENTS

fig 8

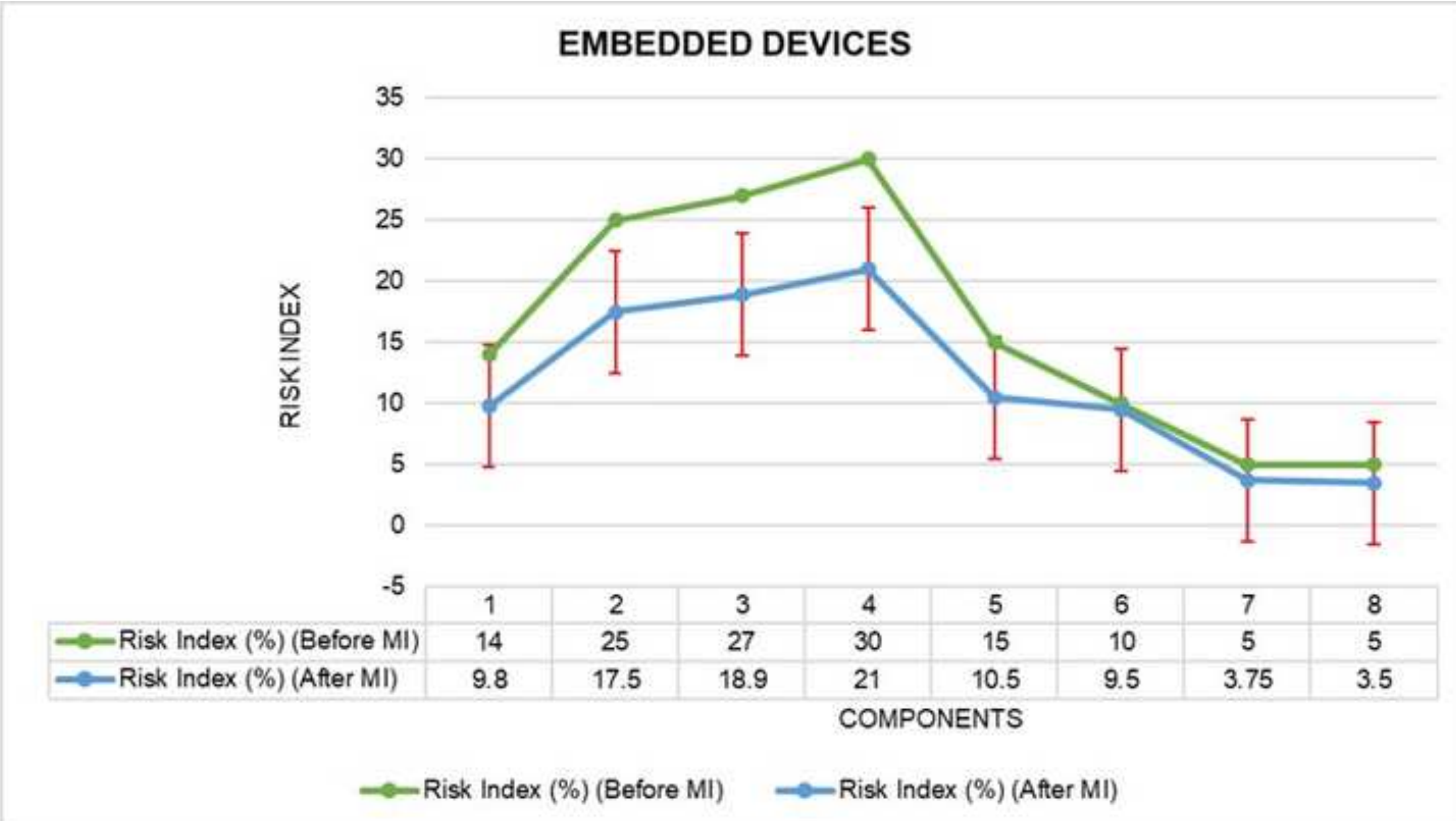

EMBEDDED DEVICES
35
30
25
20
15
10
5
0
-5
RISK INDEX
	1	2	3	4	5	6	7	8
Risk Index (%) (Before MI)	14	25	27	30	15	10	5	5
Risk Index (%) (After MI)	9.8	17.5	18.9	21	10.5	9.5	3.75	3.5
COMPONENTS
Risk Index (%) (Before MI)
Risk Index (%) (After MI)

fig 9

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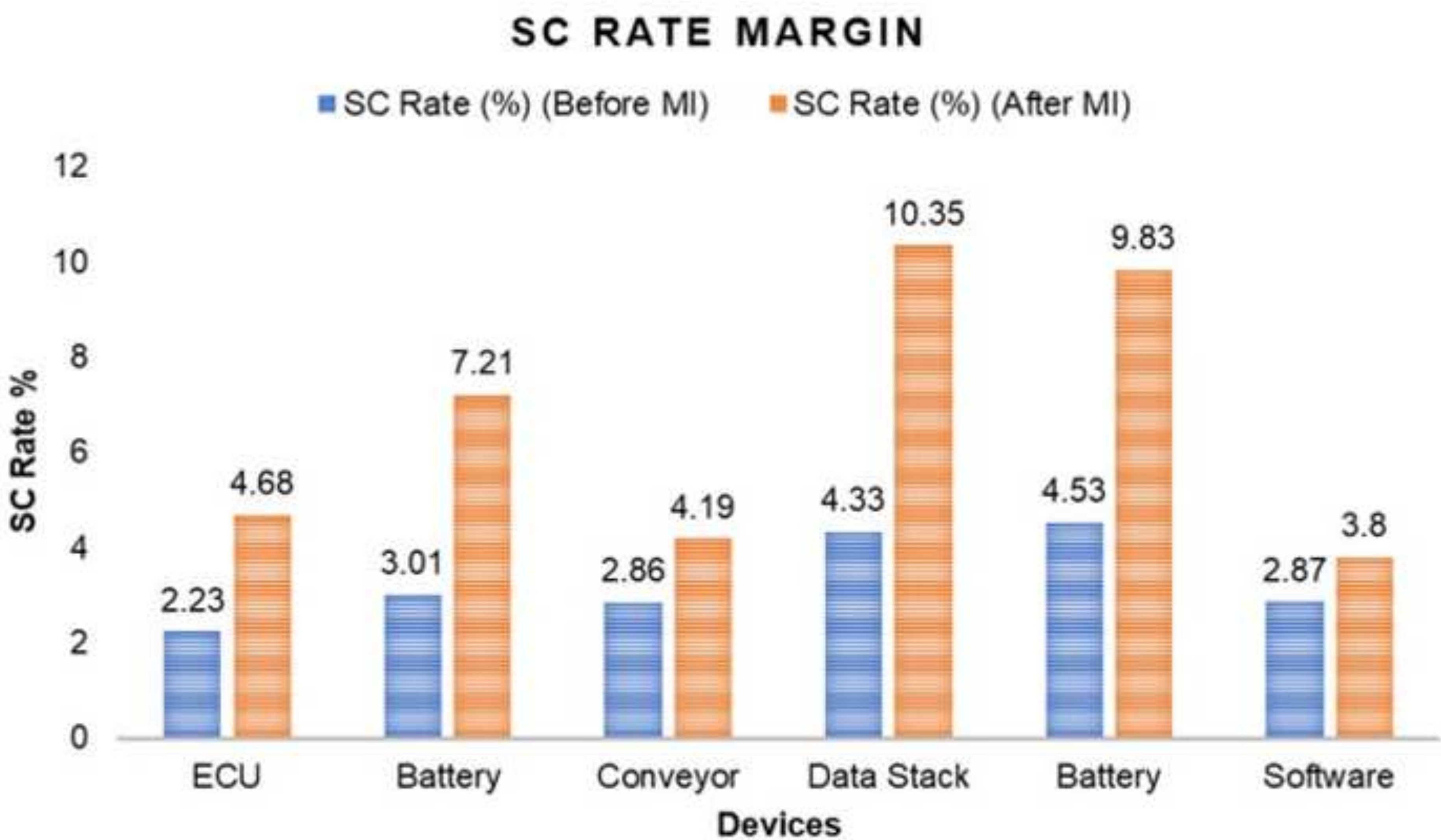

fig 10

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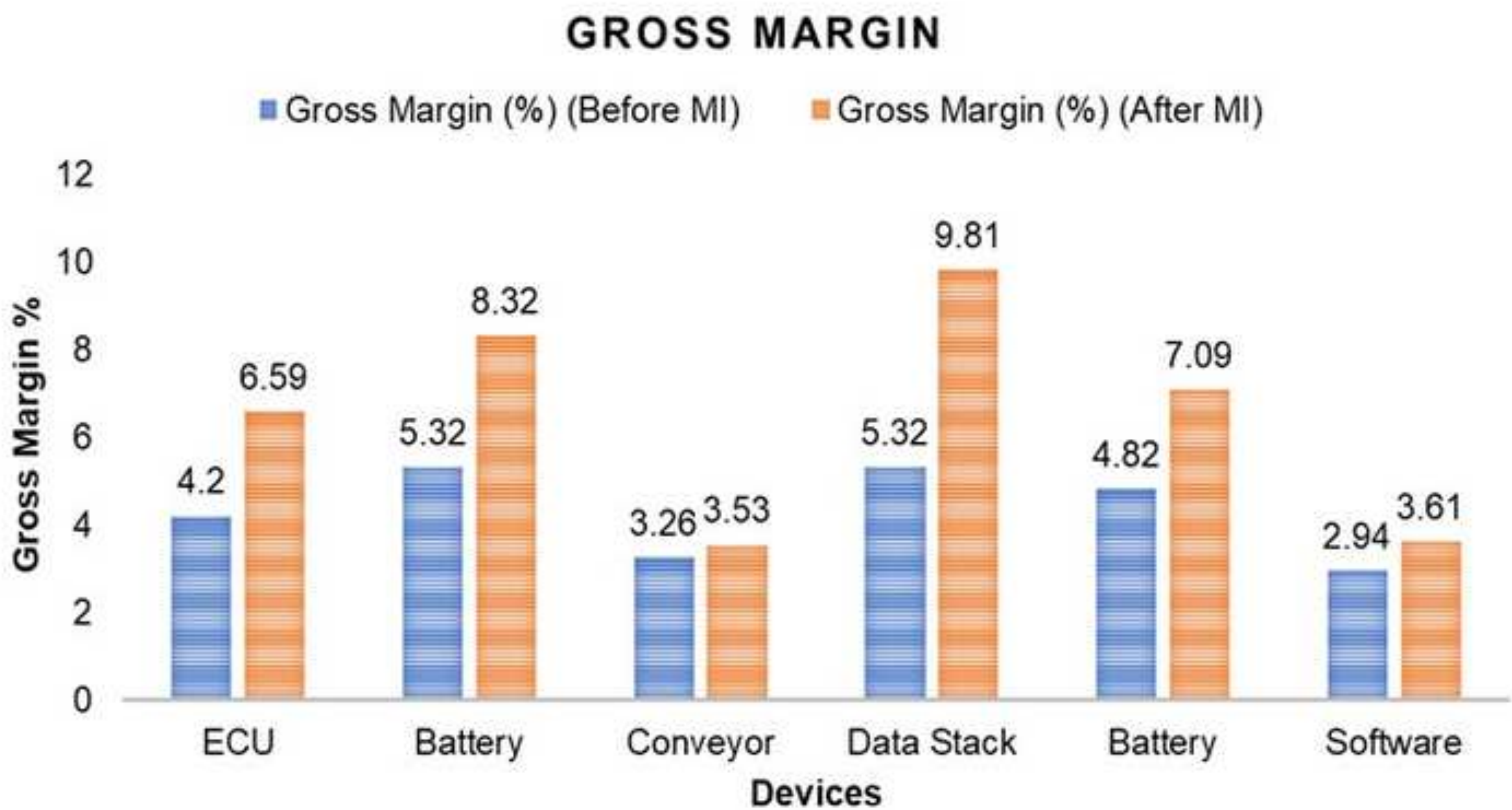

fig 11

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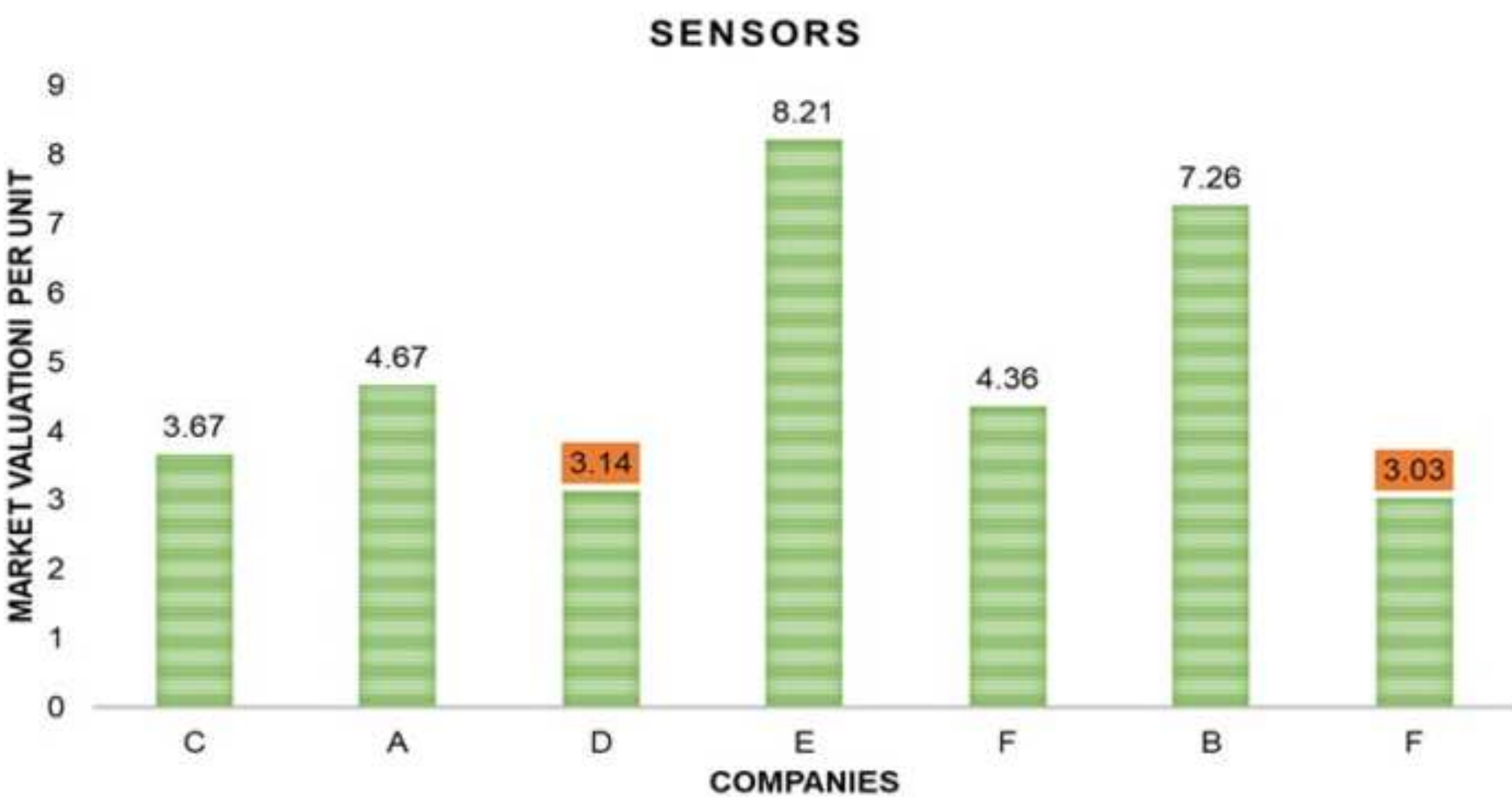

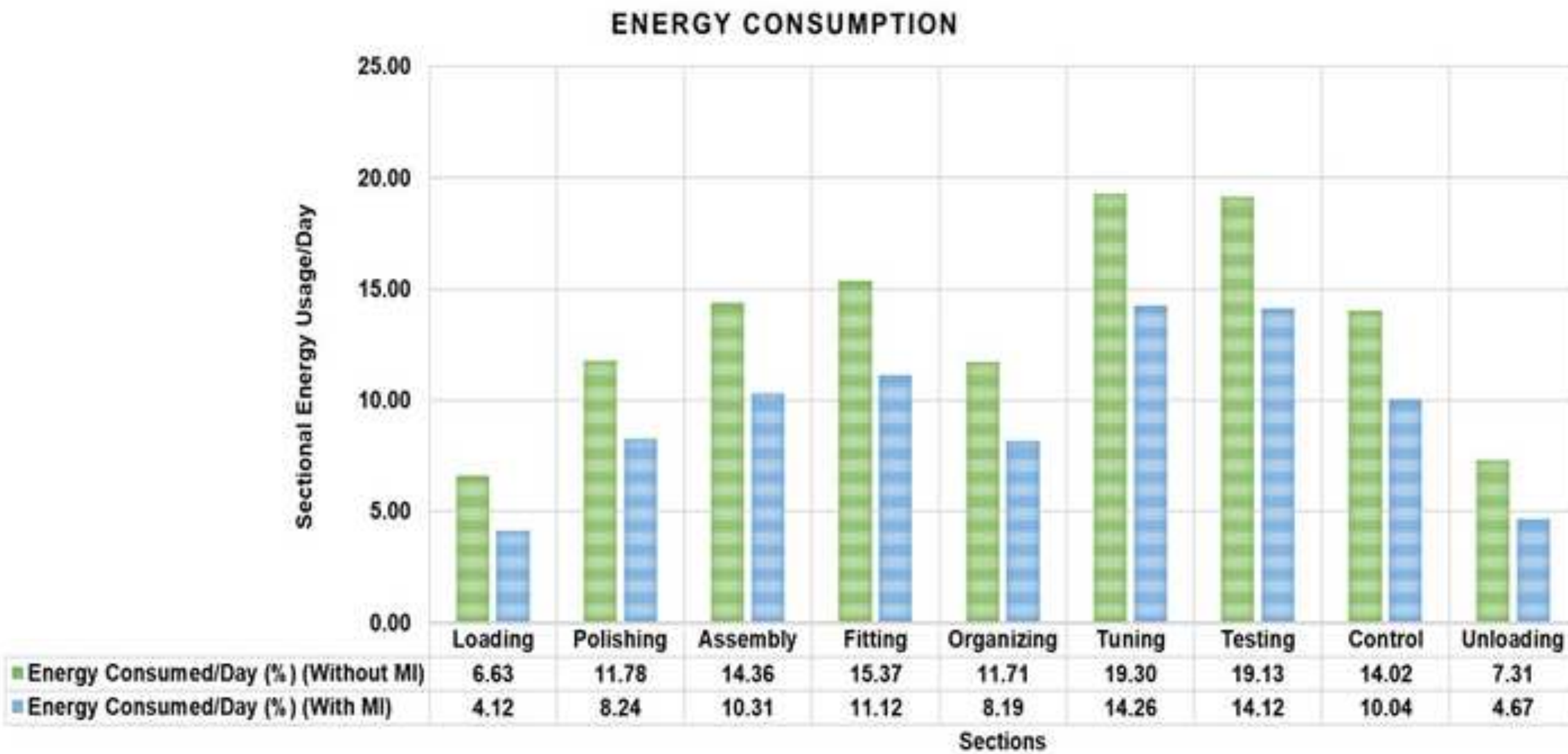
ENERGY CONSUMPTION
Sectional Energy Usage/Day
25.00
20.00
15.00
10.00
5.00
0.00
Loading
Polishing
Assembly
Fitting
Organizing
Tuning
Testing
Control
Unloading
Energy Consumed/Day (%) (Without MI) 6.63 11.78 14.36 15.37 11.71 19.30 19.13 14.02 7.31
Energy Consumed/Day (%) (With MI) 4.12 8.24 10.31 11.12 8.19 14.26 14.12 10.04 4.67
Sections

CRediT author statement

Application of Blockchain and Smart Contracts in Autonomous Vehicle Supply Chains: An Experimental Design

- Manimuthu Arunmozhi: Investigation, Writing Original Draft, Describing Data, Formal analysis
- V. G. Venkatesh: Investigation, Supervision, Validation, Writing Original Draft, Describing Data, Formal analysis, Review & Editing, Project administration
- Sobhan Arisian* (Corresponding Author): Investigation, Validation, Review & Editing, Project administration
- Yangyan Shi: Investigation, Describing Data, Validation, Review & Editing
- V. Raja Sreedharan: Investigation, Describing Data, Validation, Review & Editing