ASSOCIAÇÃO DE POLITÉCNICOS DO NORTE **(APNOR)**

INSTITUTO POLITÉCNICO DE BRAGANÇA

Towards a Functional Architecture for Integrating AI Techniques to Enhance KPI Management and Production Performance: A Mechatronics Industry Perspective

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Final Dissertation submitted to *Instituto Politécnico de Bragança.*

To obtain the master's degree in management, Specialisation in Business Management

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***Bragança*, June, 2025**

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Abstract

In the rapidly evolving mechatronics industry, optimizing manufacturing productivity is essential for maintaining competitiveness and sustainability. This research aims to develop a functional architecture that integrates AI technologies, such as machine learning and predictive analytics, to improve KPI management. The framework seeks to enhance KPI management by optimizing individual performance metrics and promoting collaboration among companies to share experiences and results.

The study will validate three key hypotheses about the impact of AI-driven KPI management on production performance, decision-making, and sustainability. The first hypothesis (H1) explores whether AI-driven KPI management frameworks lead to improvements in operational efficiency, quality, and productivity, using regression analysis of data from IoT sensors that monitor machine performance.

The second hypothesis (H2) examines how predictive analytics and machine learning models in KPI systems enhance real-time decision-making. Time-series analysis and neural networks will be applied to data from ERP and MES systems to assess decision-making improvements.

The third hypothesis (H3) investigates the integration of ecological KPIs using Life Cycle Assessment (LCA) tools. Econometric models, such as the Cobb-Douglas production function, will be used to quantify the impact of green manufacturing practices on production efficiency and sustainability.

The results provide actionable insights for stakeholders, demonstrating how integrating AI technologies into a KPI framework can significantly improve productivity and sustainability in the mechatronics sector.

Keywords: AI techniques, KPI management, predictive analytics, machine learning, sustainability

Resumo

Na indústria mecatrónica em rápida evolução, a otimização da produtividade na produção/fabrico, é essencial para manter a competitividade e a sustentabilidade das unidades fabris. Este trabalho de investigação pretende desenvolver uma arquitetura funcional que integra tecnologias de Inteligência Artificial (IA), como por exemplo a aprendizagem automática e análises preditivas, para melhorar a gestão de Key Performance Indicators (Indicadores de desempenho) (KPI). O framework pretende aprimorar a gestão de KPI ao otimizar métricas de desempenho individuais e promover a colaboração entre empresas para partilhar experiências e resultados.

O estudo validou três hipóteses-chave sobre o impacto da gestão de KPI baseada em IA no desempenho da produção, na tomada de decisão e na sustentabilidade. A primeira hipótese (H1) explora se estruturas de gestão de KPI baseadas em IA conduzem a melhorias na eficiência operacional, qualidade e produtividade, utilizando análise de regressão de dados de sensores IoT (Internet of Things) que monitoram o desempenho das máquinas.

A segunda hipótese (H2) analisa como modelos de aprendizagem automática e análises preditivas em sistemas de KPI melhoram a tomada de decisão em tempo real. Análises de séries temporais e redes neurais serão exploradas, com aplicação a dados de sistemas ERP e MES para avaliar melhorias na tomada de decisão.

A terceira hipótese (H3) investiga a integração de KPI ecológicos utilizando ferramentas de Avaliação do Ciclo de Vida (LCA). Modelos econométricos, como a função de produção de Cobb-Douglas, serão utilizados para quantificar o impacto de práticas de fabricação sustentável na eficiência da produção e na sustentabilidade.

Os resultados fornecerão insights acionáveis para as partes interessadas, demonstrando como a integração de tecnologias de IA em um framework de KPI pode melhorar significativamente a produtividade e a sustentabilidade no setor de mecatrônica.

Palavras-chave: técnicas de IA, gestão de KPI, análises preditivas, aprendizado de máquina, sustentabilidade

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AMANI KHELIA

"Difficult roads often lead to beautiful destinations."

Zig Ziglar.

Abbreviations and Acronyms

AI : Artificial Intelligence

ARM : Adaptive Resource Management

AI a aS : AI as a Service

AAS : Asset Administration Shells

CNN: Convolutional Neural Networks

DLSP : Deep Learning-based Stream Processing

DES : Discrete Event Simulation

ERP : Enterprise Resource Planning

EPR : Extended Producer Responsibility

GDP : Gross Domestic Product

iSTS : Intelligent Socio-Technical Systems

IoT : Internet of Things

IT : information technology

IEEE : Institute of Electrical and Electronics Engineers

ISO : International Organization for Standardization

IIRA : Industrial Internet Reference Architecture

KPI : Key Performance Indicator

LCA : Life Cycle Assessment

LSTM : Long Short-Term Memory (a type of neural network)

MES : Manufacturing Execution System

MAE : Mean Absolute Error

MBSE : Model-Based Systems Engineering

MFA: Multi-factor authentication

OEE : Overall Equipment Effectiveness

OT :operational technology

PdM : Predictive Maintenance

PSS: Product-Service System

PSM: Purchasing and Supply Management

RMSE : Root Mean Square Error

RAMI 4.0 : Reference Architecture Model Industry 4.0

RBAC: Role-based access control

RUL : Remaining Useful Life

SOA : Service-Oriented Architectures

STS : Socio-Technical Systems

SMEs - Small and Medium Enterprises

SVMs : Support Vector Machines

TPM : Total Productive Maintenance

UTAUT : Unified Theory of Acceptance and Use of Technology

XAI : Explainable AI

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Introduction

The mechatronics sector faces growing pressure to streamline production processes to remain competitive and sustainable due to rapid technological advancements. A transformative strategy involves integrating artificial intelligence (AI) into key performance indicator (KPI) management systems. This integration optimizes manufacturing processes and aligns traditional KPI systems with Industry 4.0 trends. This dissertation proposes a functional architecture that combines AI methodologies, such as machine learning and predictive analytics, to improve production performance and KPI management in the mechatronics industry.

This study examines the integration of AI into KPI management systems, addressing both technical advancements and managerial challenges specific to the mechatronics industry. The proposed framework enhances operational efficiency, supports real-time decision-making, and promotes sustainability, addressing critical needs in modern manufacturing environments. Moreover, it fosters collaboration among enterprises by facilitating the sharing of insights and results, thereby bridging technical implementation with tangible business value.

This research is focused on creating a functional architecture that is both scalable and modular, allowing for flexible expansion and easy adaptation to changing industry needs. By customizing solutions to meet particular requirements and ensuring interoperability with larger corporate systems, this design enables enterprises to deploy solutions gradually. The adaptability of the framework ensures its applicability across diverse industries, from healthcare to agriculture. The architecture plays a central role in supporting operational efficiency, real-time decision-making, and sustainability goals, serving as the cornerstone of this research. It aims to validate three key hypotheses about how AI-driven KPI management impacts operational efficiency, real-time decision-making, and sustainable practices.

The following are the research questions that are driving this study:

1. How can AI techniques improve the efficiency and productivity of KPI management in the mechatronics industry?
2. How do predictive analytics and machine learning mechanisms enhance the precision and timeliness of decision-making in production systems?
3. What is the role of ecological KPIs in promoting sustainable manufacturing practices, and how can they be integrated into AI-driven frameworks?

To address these questions, a multi-methodological approach will be employed, leveraging synthetic and real-world datasets, statistical analysis, and advanced visualization tools.

The dissertation is organized into five chapters:

- **Section 1: Literature Review**

  Reviews existing AI-driven KPI frameworks, critically evaluating their theoretical foundations, applications, and limitations. It identifies significant research gaps in the mechatronics industry, particularly regarding real-time processing, scalability, and sustainability. By analyzing frameworks like RAMI 4.0, IIRA, and Data Mesh, the literature review highlights opportunities for enhancing operational efficiency, predictive maintenance, and ecological KPI integration.

- **Section 2: Research methodology**

  Outlines the systematic approach used to develop and validate the AI-driven KPI framework. It includes the generation of synthetic datasets reflecting real-world scenarios, simulation-based testing, and the use of performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), F1-score, and t-tests. Benchmark comparisons against established datasets (e.g., NASA Bearing Dataset, UCI Hydraulic System) .

- **Section 3:Framework Development**

  Introduces the novel AI-driven KPI framework, detailing its core modules for predictive maintenance, real-time decision-making, and ecological KPI integration. Implementation challenges, such as data quality, system integration, and legacy system compatibility, are discussed alongside proposed solutions. The modular architecture ensures adaptability across diverse industries, addressing both technical and managerial needs.

- **Section 4: Results and Visualization**

  Presents empirical results and visualizations using both synthetic and real-world datasets (e.g., NASA Bearing Dataset, UCI Hydraulic System) , demonstrating measurable improvements in key performance indicators such as Overall Equipment Effectiveness (OEE), unplanned downtime reduction, and carbon footprint optimization. Visualizations, including managerial dashboards, highlighting the framework's ability to support strategic planning and sustainability goals.

Through this structured approach, the dissertation effectively aligns its methodology and findings with the stated research objectives, demonstrating how integrating AI technologies into KPI management systems directly leads to improvements in both operational efficiency and sustainability in the mechatronics sector.

1. Literature review

1.1. General Context

The mechatronics sector is a cornerstone of modern production, integrating computer science, electronics, mechanical engineering, and control systems to improve automation, precision, and flexibility. This interdisciplinary approach enables higher performance levels in dynamic and competitive manufacturing environments, driving innovation and efficiency (Wuest et al.2016). Key Performance Indicators (KPIs) remain critical for evaluating productivity, operational efficiency, and strategic alignment. These metrics track important factors like equipment availability, failure rates, energy use, and throughput, offering valuable insights for decision-making and continuous enhancement.

Despite their significance, traditional KPI systems frequently lack the agility required in dynamic manufacturing contexts. Challenges such as the absence of sustainability indicators, siloed data systems, and data latency impede responsiveness and informed decision-making. As highlighted by (Bhatti et al., 2014), industrial processes increasingly rely on real-time, high-quality data, yet many companies lack the mechanisms to leverage this information effectively. For instance, unplanned downtime in critical industries such as automotive can result in costs as substantial as $2.3 million per hour (Siemens, 2024). These challenges highlight the necessity for KPI systems integrated with AI, providing cross-functional integration and predictive abilities.

The objective of this literature review is to conduct a critical evaluation of the existing AI-driven KPI systems in the mechatronics industry, with a focus on identifying gaps and opportunities for enhancement. It will explore the theoretical foundations, applications, and frameworks guiding AI-KPI integration, as well as the challenges and limitations faced in implementation (Pham & Afify, 2005).

By integrating current research, this review aims to align with the research goals and queries of the dissertation, particularly emphasizing how AI can improve KPI management for enhanced operational efficiency, sustainability, and real-time decision-making (Jain, 2024). The review is structured into main sections focusing on predictive maintenance, quality control, sustainability optimization, and digital twin technology. It includes an analysis of frameworks such as RAMI 4.0, IIRA, and Data Mesh. Together, these sections provide a comprehensive understanding of the transformative potential of AI-driven KPI systems and highlight areas requiring further investigation.

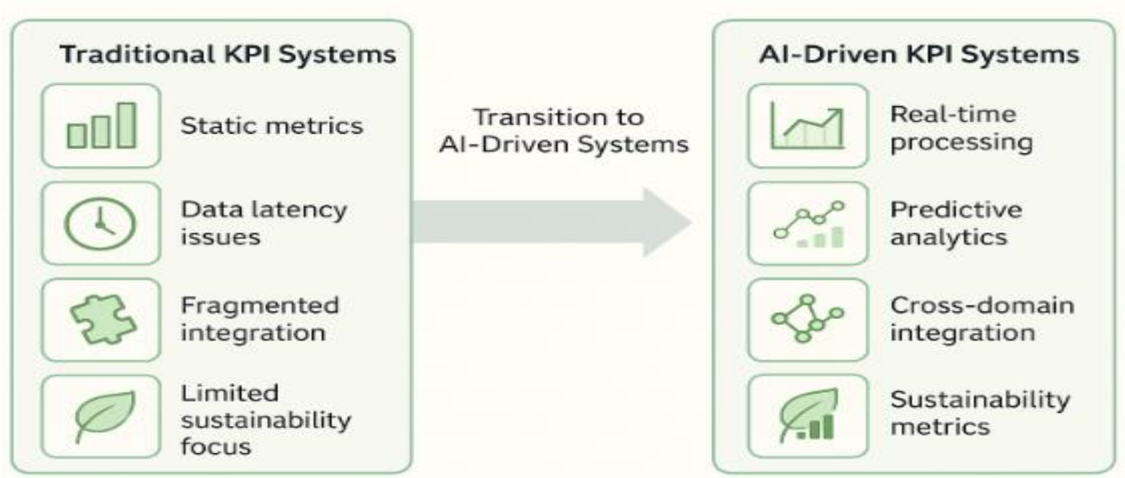

Figure 1. Overview of KPI Framework in Manufacturing.

Source: Author's own elaboration.

1.2. Specific Focus on KPI Frameworks

In smart factories networked, real-time dynamics are difficult for legacy KPI systems to grasp. Legacy systems are rigid, divided into compartments, and not suitable for analyzing intricate data streams, leading to fragmented insights. Static performance measurements face challenges in adapting to changing circumstances, such as interruptions in supply or variations in quality. Moreover, as highlighted by Bhatti et al., (2014), the importance of preprocessing and data quality for successful AI integration is emphasized, where issues like inconsistent data, missing values, and unstructured formats impede machine learning applications.

With the use of adaptive data models and predictive analytics, modern techniques aim to overcome these limitations. Digital twins, which are virtual representations of physical systems, are being used more and more to improve maintenance, reduce downtime, and simulate performance scenarios using predictive modeling Adesina et al. (2024).By utilizing real-time information, these solutions improve responsiveness, facilitate problem identification, and cut waste.

Intelligent KPI systems are currently primarily made possible by artificial intelligence techniques like neural networks, reinforcement learning, and supervised machine learning. As an example, support vector machines (SVMs) are frequently employed for tool condition evaluation and quality monitoring, attaining great accuracy in fault prediction and detecting defects (Wuest et al., 2016). Time-series data may also be temporally modeled using deep learning techniques like convolutional neural networks and LSTMs, which enable real-time pattern identification and predictive control (Grupta, 2022).

AI systems enhance efficiency across the life cycle, reduce industrial waste, and optimize energy usage, aligning with sustainability objectives. Big data analytics and AI-powered monitoring systems, for instance, have made it possible to significantly reduce costs and emissions in industries like battery and semiconductor production. Despite advancements, the full integration of AI into traditional KPI systems often faces obstacles, primarily stemming from organizational and structural resistance (Graham et al., 2015).

Table 1. Comparison of Traditional and AI-Driven KPI Systems.

ASPECT	TRADITIONAL KPI SYSTEMS	AI -DRIVEN KPI SYSTEM
Data Processing	Static, periodic reporting	Real-time analysis and predictive modeling
Flexibility	Inflexible, compartmentalized	Adaptive, capable of handling complex data streams
Decision Making	Reactive, delayed responses	Proactive, real-time insights
Sustainability	Limited focus on ecological metrics	Optimizes energy use and reduces waste
Integration	Fragmented data silos	Seamless integration of IoT, PLCs, and CNC data

Source: Author's own elaboration based on Wang and Aviles (2023,p283).

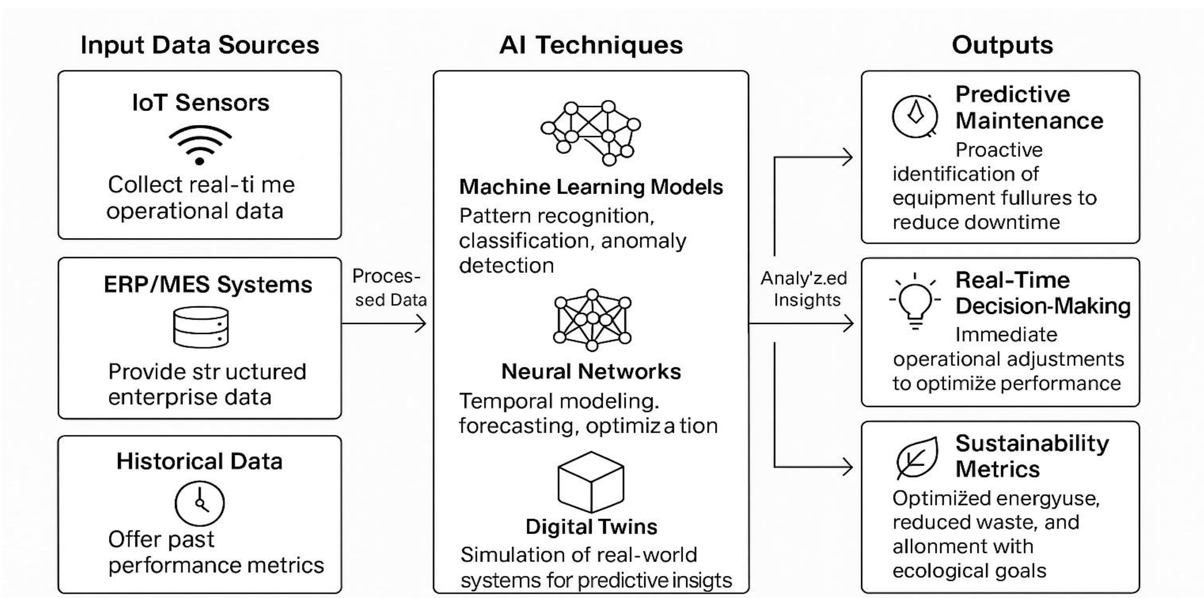

Figure 2. Integration of AI Techniques into KPI Frameworks.

Source: Author's own elaboration.

Moving from traditional KPI systems to AI-driven frameworks signifies a fundamental change in how manufacturers handle performance monitoring, decision-making, and sustainability. AI-driven KPI systems use advanced techniques like predictive analytics, digital twins, and machine learning to overcome the limitations of legacy systems, which suffer from rigidity, fragmented insights, and restricted adaptability. These technologies enable companies to eliminate waste, optimize operations, and meet the ever-changing demands of Industry 4.0 by facilitating real-time data processing, proactive decision-making, and the smooth integration of IoT and sustainability indicators.

Table 1 illustrates the benefits of AI-driven KPI systems. However, in order to fully realize their potential, issues like organizational inertia and legacy system compatibility must be resolved. Furthermore, Figure 2 shows the integration of AI techniques into KPI frameworks, emphasizing the progression from input data sources to actionable outputs, including sustainability measurements, real-time decision-making, and predictive maintenance. Ultimately, this evolution demonstrates the need for a comprehensive architecture that synchronizes performance monitoring with real-time intelligence and sustainability, paving the way for smarter, more efficient manufacturing ecosystems.

1.3. Applications of Artificial Intelligence in KPI Management

Artificial Intelligence (AI) has become a transformative force in industrial operations by enabling data driven decision making , enhancing operational efficiency , and integrating sustainability into core business processes.By utilizing AI technologies like machine learning, deep learning, and edge computing, organizations can derive actionable insights from large datasets, leading to tangible enhancements in production, maintenance, and environmental practices. Three key areas where AI significantly impacts Key Performance Indicator (KPI) management are Predictive Maintenance , Quality Control , and Sustainability Optimization .

1.3.1. Predictive Maintenance: Revolutionizing Equipment Management

Predictive Maintenance (PdM) leverages IoT sensors, machine learning models, and real-time analytics to anticipate equipment failures before they occur. This proactive approach not only reduces unplanned downtime estimated to cost manufacturers between 5% and 20% of annual revenue by up to 30%, (Mobley, 2002), extends equipment lifespan by 20–25%, and improves overall system reliability. The integration of AI into PdM enables systems to detect anomalies, estimate Remaining Useful Life (RUL), and recommend optimal maintenance schedules based on real-world conditions rather than fixed intervals.

The implementation of Predictive Maintenance (PdM) comes with various challenges, including substantial initial setup expenses that create financial obstacles, especially for small and medium-sized enterprises (SMEs) (Serradilla, Zugasti, & Zurutuza, 2020).Additionally, many industrial facilities operate with legacy systems that lack compatibility with modern AI-driven tools, creating technical hurdles during integration. Furthermore, industrial data quality issues, such as sensor noise or missing values, can compromise the accuracy of predictive models (Nunes, Santos, & Rocha, 2023).

To overcome these challenges, organizations are turning to hybrid AI models that merge physics-based degradation models with machine learning algorithms to enhance((Mansa et al., 2020). Remaining Useful Life (RUL)predictions. Employing modular implementation strategies and leveraging government-supported subsidies or grants can assist small and medium-sized enterprises (SMEs) in overcoming financial limitations, thereby increasing accessibility to Predictive Maintenance (PdM). These strategic interventions ensure that AI-powered predictive maintenance delivers long term value while supporting resilient and adaptive manufacturing ecosystems (Patel, Vasa, & Patel, 2023).

Table 2. Challenge of Predictive Maintenance.

CHALLENGE	IMPACT	SOLUTION
High initial setup costs	Financial barriers of SMEs	Modular implementation, subsidies
Legacy system compatibility	Difficult integration with older systems	Middleware solutions , retrofitting kits
Data quality issues	Errors in prediction accuracy	Robust preprocessing techniques

Source: Adapted from Nunes et al. (2023,p58).

1.3.2. Quality Control: Enhancing Precision and Efficiency

AI-driven quality control systems, particularly those employing convolutional neural networks (CNNs), have achieved defect detection rates that can reach 99.5% (Ming et al., 2017) . This success significantly surpasses traditional inspection methods. AI-driven systems automate visual inspections, ensuring consistent product quality and reducing human error. For example, Toyota implemented AI-driven robotics to reduce defects by 30%, demonstrating the tangible impact of AI operational excellence (Embarka, Reggani, Haddadi, & Messai, 2024).

Despite these advancements, challenges persist false positives and high computational resource demands remain significant hurdles. Training deep learning models requires extensive labelled datasets, which are not always available. Real-world data often includes noise and anomalies that can affect model performance, requiring robust preprocessing techniques. Current methodologies often miss considering interactions between components in predictive models, which are essential for improving system accuracy. (Nunes et al.,2023). Detecting anomalies caused by sensor malfunctions or external disturbances is crucial to avoid misinterpretations. However, only a few approaches explicitly focus on distinguishing noise from relevant abnormal data.

To reduce delays and enhance quick decision-making, AI-driven quality control systems are now being combined with edge computing systems to enhance performance. Edge-based AI systems process data locally, reducing the computational burden on centralized cloud systems. This integration enables faster response times and enhances the scalability of quality control systems across manufacturing environments. However, sensor integration remains a significant bottleneck, as noted in studies focusing on industrial IoT applications.

Hardware infrastructure demands, including imaging equipment and processing capabilities, are among the technical challenges that must be addressed during implementation. To ensure the reliability of AI-driven quality control systems, systematic model validation processes and a strong commitment to data quality management are essential for maintaining accuracy. These practices are essential for maintaining the accuracy and effectiveness of automated inspection systems in dynamic industrial settings.

The combination of advanced AI algorithms, edge computing, and robust data management practices has resulted in substantial improvements in inspection accuracy, reduced manual inspection requirements, and enhanced detection of subtle defects across various industrial applications. The transformative potential of these advancements in AI for quality control is demonstrated while also highlighting the need for careful planning and implementation to overcome technical and operational challenges.

Table 3. Technology of Quality control.

TECHNOLOGY	ADVANTAGE	CHALLENGE
Cloud computing	Centralized processing, scalable storage	High latency
Edge computing	Faster response times, reduced latency	Limited hardware resources

Source :Adapted from Martínez-Arellano and Ratchev (2024,p172).

1.3.3. Sustainability Optimization: Aligning Operational Excellence with Environmental Responsibility

AI plays a pivotal role in sustainability by optimizing energy consumption, reducing waste, and integrating ecological Key Performance Indicators (KPIs) (Sarancic et al., 2023). For instance, Boeing’s AI-driven design optimization reduced production lead times by 25% , while Bosch’s application of Life Cycle Assessment (LCA) tools cut greenhouse gas emissions by 15% (Bosch Sustainability Report, 2024) . Similarly, Tesla has made significant strides in sustainable manufacturing practices, particularly in battery production and recycling.

Tesla has reduced energy use by more than 70% and the carbon impact of battery manufacturing by switching to in-house-manufactured 4680 cells. Along with implementing a closed-loop recycling system, the firm was able to recover valuable materials from production scrap and end-of-life batteries, producing over 50 tons of recycled material every week (Tesla Impact Report,2021).

Despite these promising results, integrating ecological KPIs into manufacturing systems remains underdeveloped and requires extensive cross-sector collaboration .The exponential growth of data needing processing, storage, and analysis presents specific challenges, especially when real-time actions are required (Nunes et al., 2023). Current models often lack sufficient integration of physical and knowledge based approaches, which could enhance sustainability efforts emphasize the importance of thoughtfully integrating sustainability considerations during early-stage Product-Service System (PSS) design. This includes focusing on traceability, adaptability, and the ability to upgrade infrastructure, as well as fostering employee empowerment and job satisfaction.

Additionally, achieving optimal computational and predictive performance in AI systems requires addressing real-time and flexibility requirements in modern industries (Nunes et al., 2023). Adaptive resampling-based particle filtering methods, for example, can enhance tool life prediction accuracy but necessitate careful calibration and validation,stresses the importance of aligning AI-driven improvements with broader sustainability goals, including extended producer responsibility (EPR) and circular economy principles, which current OEE focused AI systems often overlook.

Table 4. Sustainability Metrics.

SUSTAINABILITY METRIC	EXAMPLE	IMPACT
Energy consumption	Dry electrode process in battery production	Reduced energy use by >70%
Waste reduction	Closed-loop recycling system	Recovery of critical materials

Source: Adapted from European Economic and Social Committee(2020).

1.4. Digital Twin Technology: Bridging Physical and Virtual Worlds

Digital twin technology creates virtual representations of physical systems, enabling real-time monitoring, predictive analysis, and process optimization. This technology improves predictive maintenance by simulating possible failures in advance, reducing downtime, and optimizing operations without interrupting actual workflows (Tao et al., 2018). Additionally, digital twins enable organizations to test scenarios, evaluate performance improvements, and make data-driven decisions in near real-time. For example, Rio Tinto, a global mining company, uses digital twin systems to explore methods for enhancing production efficiency without risking equipment or operations (Attaran & Çelik, 2023).

However, despite its transformative potential, digital twin technology faces several challenges that hinder its widespread adoption. Ensuring real-time synchronization between physical and digital systems remains a significant hurdle, as delays in data processing can compromise the accuracy of simulations and predictions ((Li, Wei, & He, 2018). Integrating diverse data sources further complicates deployment, particularly in industries with legacy systems that lack compatibility with modern digital twin platforms (Tao et al., 2018). Moreover, collecting, transmitting, and processing large volumes of data in a timely manner adds complexity to deploying digital twins across various industrial scenarios (Nunes et al., 2023). The lack of standardization across platforms exacerbates these challenges, making seamless integration difficult .

In addition to technical and operational challenges, highlights that digital twin implementation often neglects broader use contexts, such as regulatory, normative, and cognitive factors, limiting its effectiveness in service-oriented business models (Sarancic et al., 2023). For example, regulatory compliance requirements may necessitate specific data handling practices that digital twin systems fail to address adequately. Similarly, normative factors, such as organizational culture and employee acceptance, can influence the adoption and success of digital twin technologies. Cognitive factors, including the interpretability of data and decision-making processes, also play a crucial role in ensuring that digital twins deliver actionable insights rather than overwhelming users with complex information.

Moreover, small and medium enterprises (SMEs) encounter extra obstacles since deploying sophisticated digital twin systems may demand significant investments in hardware upgrades and software adjustments, which can be costly. (Thramboulidis, 2018)emphasizes the importance of domain-specific architectural patterns to address scalability, collaboration, and security concerns. However, these solutions often introduce additional complexity, particularly for organizations with limited resources or outdated IT infrastructure.

To overcome these challenges, advancements in artificial intelligence (AI), the Internet of Things (IoT), and cloud computing are playing a pivotal role in enhancing digital twin capabilities. AI-powered digital twins can replicate intricate real-world systems by using data from IoT devices, constantly pinpointing areas for enhancement and aiding in practical decision-making. For instance, digital twins in manufacturing are increasingly used to monitor production lines, optimize supply chain operations, and provide remote assistance for asset management and maintenance (Grieves & Vickers, 2017).

Table 5. Challenges of Digital Twin Technology.

CHALLENGE	IMPACT	SOLUTION
Real-Time Synchronization	Delays in data processing	Advanced IoT sensors, edge computing
Legacy System Integration	Technical hurdles	Middleware, retrofitting strategies
Data Standardization	Lack of interoperability	Adoption of industry -wide standards
Scalability and Collaboration	Complexity in implementation for SMEs	Cloud-based solutions, modular architectures
Broader Use Contexts	Neglect of regulatory, normative, cognitive factors	Domain-specific frameworks, user-centric design

Source : Author's own elaboration.

1.5. AI-Driven Improvements in Overall Equipment Effectiveness (OEE)

Artificial Intelligence (AI) is revolutionizing the enhancement of Overall Equipment Effectiveness (OEE) by facilitating real-time monitoring, predictive maintenance, and process optimization. Machine learning models analyze historical production data to uncover inefficiencies and suggest corrective actions, thereby improving equipment availability, performance, and product quality(Muchiri & Pintelon, 2018). For instance, AI-driven systems can anticipate equipment failures before they happen, cutting down on unplanned downtime and reducing waste. This proactive strategy aligns with frameworks like Total Productive Maintenance (TPM), which stress continuous improvement and efficiency gains .

Nevertheless, deploying AI solutions across multiple production lines poses a significant challenge. These implementations are resource heavy and demand specialized expertise, especially when dealing with legacy systems that lack compatibility with modern AI tools(Pintelon & Gelders, 1992). Moreover, the limited generalization of prognostic models hampers their effectiveness in dynamic industrial settings where flexibility and adaptability are crucial (Nunes et al., 2023). To tackle these issues, future research should investigate the integration of computational resources from cloud and edge devices to enable real-time decision-making and boost predictive accuracy.

Beyond technical hurdles, it's vital to align AI-driven improvements with broader sustainability goals. (Sarancic et al., 2023) highlight the necessity of incorporating principles such as extended producer responsibility (EPR) and circular economy practices into AI systems. Current OEE-focused solutions often neglect these aspects, revealing a gap between operational efficiency and sustainable manufacturing practices. Bridging this gap calls for a comprehensive approach that merges AI with lean methodologies and continuous improvement frameworks.

Recent advancements in Overall Equipment Effectiveness (OEE) frameworks highlight the significant impact of integrating methodologies like Total Productive Maintenance (TPM) in boosting equipment efficiency. For instance, in the electronics industry, companies achieved OEE improvements ranging from 20% to over 40%, with some cases surpassing 85% after TPM implementation. Similarly, some studies show that manufacturers witnessed a remarkable rise in OEE, underscoring TPM's effectiveness in reducing losses and enhancing plant uptime (Nallusamy, Kumar, Yadav, & Prasad, 2018). Additionally, a locomotive component supplier reported a 30% increase in OEE, driven by improvements in availability, performance, and quality rates. These case studies demonstrate the dual role of OEE as both a diagnostic tool and a performance metric, guiding targeted interventions to address inefficiencies. By combining TPM with continuous improvement practices like Kaizen, organizations can not only achieve world-class OEE levels but also sustain and further enhance them, ensuring long-term operational excellence (Kasim, Musa, Razali, Noor, & Saidin, 2015).

1.6. Existing Frameworks for AI-KPI Integration in Mechatronics

The integration of artificial intelligence (AI) into Key Performance Indicator (KPI) management plays a pivotal role in optimizing manufacturing processes, particularly in the mechatronics industry. Several architectural frameworks have been proposed to support this integration, each offering distinct advantages and limitations. This section critically reviews five major frameworks RAMI 4.0 , IIRA , Data Pipeline Architectures, Service-Oriented Architecture (SOA) , and Data Mesh to assess their relevance to mechatronics and identify gaps that hinder effective AI-driven KPI implementation.

1.6.1. RAMI 4.0: A Standardized Blueprint for Industry 4.0 Adoption

The Reference Architecture Model for Industry 4.0 (RAMI 4.0) provides a comprehensive, three dimensional framework that supports interoperability , standardization , and scalable system design across industrial environments. It structures industrial components along three key dimensions: hierarchy levels (business, information, asset), lifecycle phases (design, production, operation), and architecture layers (asset, communication, integration). By aligning these axes, RAMI 4.0 enables seamless data exchange between information technology (IT) and operational technology (OT) systems, facilitating modular development and traceable engineering practices (Oñate & Sanz, 2024). This structured approach is particularly beneficial for guiding digital transformation in industries like manufacturing, supply chain management, and automation based on blockchain technology.

A major strength of RAMI 4.0 is its ability to promote standardization , which is crucial for integrating heterogeneous systems and ensuring consistency across platforms. It also supports Model-Based Systems Engineering (MBSE), allowing for systematic documentation and traceability throughout the product lifecycle. The framework has been successfully applied in real-world contexts, including lightweight Manufacturing Execution Systems (MES) for SMEs, fog computing, and cloud manufacturing projects.

Despite its structural advantages, RAMI 4.0 faces limitations in addressing domain-specific needs , especially in dynamic, high-mix, low-volume environments typical of mechatronics . Its abstract nature and lack of detailed implementation guidance hinder its direct application in real-time or AI-integrated systems (Melo, Godoy, Ferrari, & Sisinni, 2021). Additionally, security concerns related to cloud-based deployments under this framework further limit its effectiveness in supporting AI-driven KPI integration , making it less suitable for advanced, intelligent manufacturing applications without significant adaptation.

Table 6. Key Applications and Insights of RAMI 4.0.

APPLICATION	DESCRIPTION
MES for SMEs	Lightweight MES solutions for SMEs, ensuring communication and data sharing.
Fog Computing	Reduces processing loads and improves productivity in manufacturing

Integration	systems
OEE Analysis	Analyzes the impact of RAMI 4.0 layers on Overall Equipment Effectiveness (OEE).
PSM Adaptation	Guides Industry 4.0 adoption in Purchasing and Supply Management (PSM).
Cloud Manufacturing	Combines RAMI 4.0 with cloud technologies for modernized automation.

Sources: Adapted from Melo, Godoy, Ferrari, and Sisinni, (2021, p10).

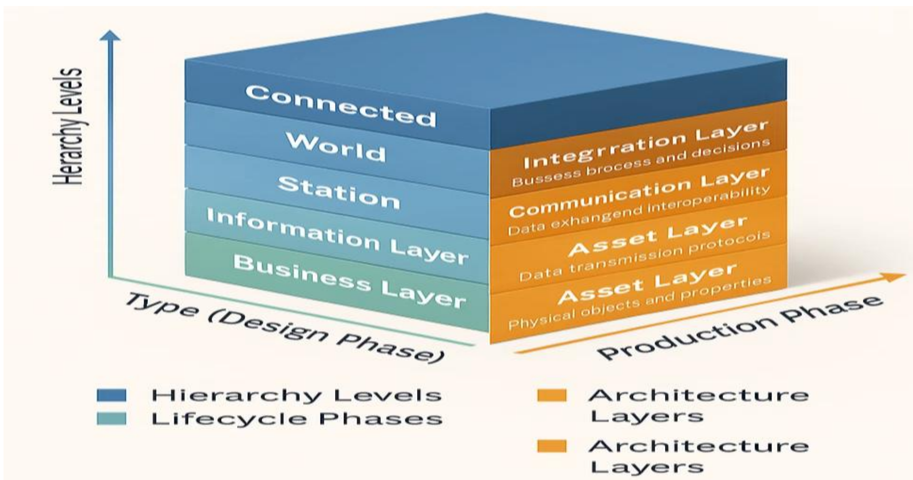

Figure 3. 3D Diagram of RAMI 4.0.

Source: Adapted from Melo, Godoy, Ferrari, and Sisinni, (2021, p6).

This diagram shows in figure 3 the three-dimensional structure of the RAMI 4.0 framework, displaying its hierarchy levels vertically, lifecycle phases horizontally, and architecture layers in depth. It provides a visual representation of how RAMI 4.0 enables interoperability and standardization across industrial systems.

1.6.1. Industrial Internet Reference Architecture (IIRA): Promoting Interoperability and Modularity

The Industrial Internet Reference Architecture (IIRA) provides a modular and stakeholder oriented framework tailored for Industrial IoT (IoT) systems. It defines four viewpoints Business, Usage, Functional, and Implementation which guide system development from goal setting to technical execution. IIRA emphasizes interoperability through widely accepted standards like IEEE , making it ideal for integrating legacy and modern systems.

Its modular architecture allows organizations to customize solutions based on specific needs while maintaining compatibility with broader enterprise systems. The framework also encourages a holistic view, fosters collaboration among stakeholders, and supports technologies such as digital twins and microservices (Pontarolli, 2023).

Despite its advantages, IIRA encounters notable difficulties in integrating AI and customizing solutions for specific domains ;it lacks explicit guidance on deploying AI models or aligning them with KPIs, which limits its applicability in dynamic manufacturing contexts. Moreover, its complexity makes it unsuitable for small and medium enterprises (SMEs) with limited technical resources. In mechatronics, where flexibility and adaptability are critical, IIRA's generic design often fails to meet the demands of high-mix, low-volume production (Rocha et al;, 2022).

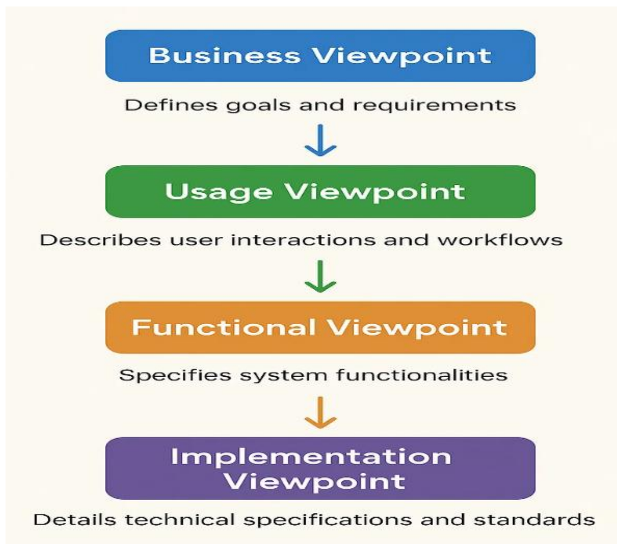

Figure 4. Four Viewpoints of IIRA and Their Role in Supporting Interoperability.

Source: Author's own elaboration.

This figure 4 illustrates how the four viewpoints of the Industrial Internet Reference Architecture (IIRA) Business, Usage, Functional, and Implementation work together to ensure interoperability across IoT systems.

1.6.2. Data Pipeline Architectures: Streamlining Data Flow for Decision-Making

Data pipeline architectures provide a systematic and organized approach to managing data throughout its lifecycle from acquisition to actionable insights. These pipelines are typically composed of three core levels: Smart Connection, which handles data ingestion from various sources such as IoT sensors and enterprise systems; Data to information Conversion, which involves processing, filtering, and enriching raw data to improve quality and relevance; and the cyber Level, where advanced analytics and simulation tools generate meaningful insights to support decision-making. This architecture is especially efficient in managing extensive datasets, facilitating centralized analytics, and maintaining data consistency. The integration of stream-processing tools like Apache Kafka and Flink further enhances performance by minimizing latency and enabling real-time data analysis, making these pipelines valuable for industrial applications (Peres et al., 2020).

Despite these strengths, traditional data pipeline architectures encounter significant challenges when applied to complex, cross-domain environments like mechatronics, where seamless interaction between physical and digital systems is essential. They often lack native support for aligning data flows with strategic business goals or AI-driven KPIs, limiting their effectiveness in dynamic manufacturing settings (Budach, 2022). Additionally, compared to more flexible and decentralized alternatives such as Data Mesh, conventional data pipelines exhibit lower scalability and adaptability in rapidly changing environments. Scalability has been improved through machine learning techniques like Deep Learning-based Stream Processing (DLSP) combined with Adaptive Resource Management (ARM) to optimize resource utilization in cloud environments (Xu et al, 2022). However, without structural enhancements, traditional data pipelines remain less suitable for highly agile Industry 4.0 ecosystems.

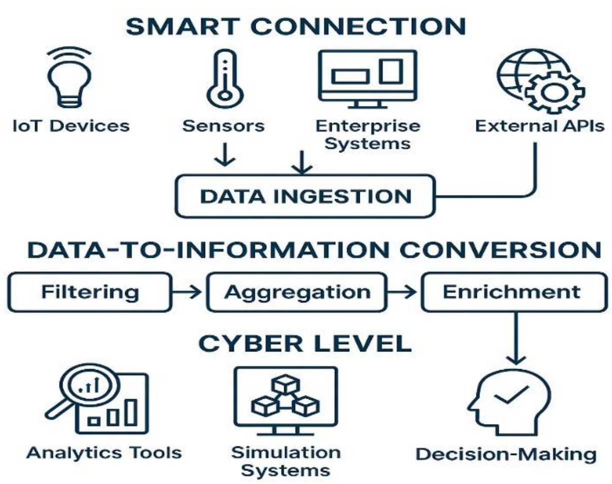

Figure 5. Three Levels of Data Pipeline Architectures: From Data Ingestion to Decision-Making.

Source: Author's own elaboration.

This figure 5 illustrates how data pipeline architectures manage data flow across three levels: data acquisition, processing, and decision support to enable data-driven manufacturing decisions in Industry 4.0 environments.

1.6.3. Service-Oriented Architectures (SOA): Promoting Modularity and Flexibility

Service-Oriented Architecture (SOA) enables flexible system design by decomposing complex functionalities into loosely coupled services accessible via standardized interfaces. This modularity supports the reuse of services, improves maintainability, and simplifies integration across various platforms (Aladwan, 2018). SOA fosters interoperability and decentralized control, this allows systems to respond dynamically to operational changes while maintaining consistency across heterogeneous environments. It also facilitates the integration of legacy systems, which is essential in organizations transitioning to Industry 4.0 technologies (Cavalieri & Salafia, 2020).

However, SOA lacks support for real-time analytics and predictive capabilities, which are essential for optimizing AI-driven KPIs and decision-making in modern manufacturing. As the number of services increases, so does the complexity of managing interdependencies, leading to challenges in governance, maintenance, and scalability (Niemann, 2008). Additionally, poorly designed interfaces can result in tight coupling, undermining the very principles of modularity and reusability that make SOA effective. Refactoring services into smaller, cohesive modules can address these issues, but it often demands expertise and investment, making it less suitable for agile or resource constrained environments like small and medium enterprises (SMEs) (Thramboulidis, 2018).

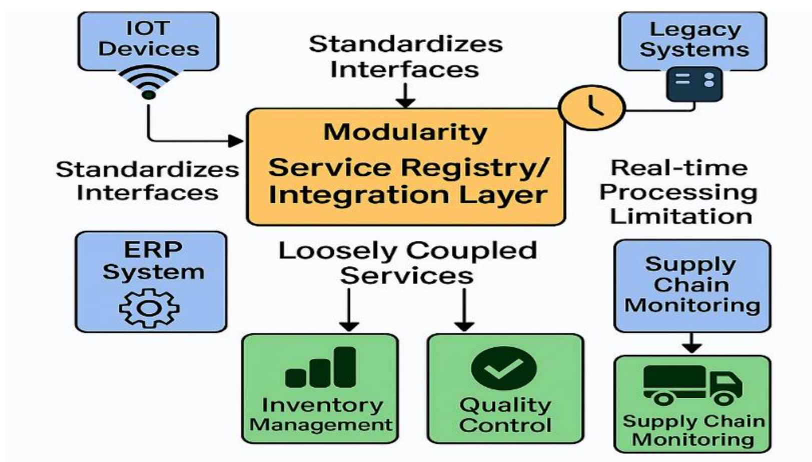

Figure 6. SOA Integration: Key Components and Limitations.

Source: Author's own elaboration.

This diagram in figure 6 illustrates how Service-Oriented Architecture (SOA) enables modularity and interoperability by connecting loosely coupled services through standardized interfaces. It also highlights SOA's limitations in real-time processing, which can be addressed with complementary technologies like edge computing or stream-processing frameworks

1.6.4. Data Mesh: Decentralized Data Management for Scalability

Data Mesh introduces a decentralized data governance model that shares ownership among business domains nearest to the data; it operates on four core principles: decentralized data ownership, data as a product, federated governance, and self-serving infrastructure that collectively enhance scalability, agility, and domain-specific flexibility (Wider, Verma, & Akhtar, 2023).By treating data as a product with clear interfaces and APIs, Data Mesh ensures curated, high-quality datasets that are independently managed by each domain, reducing bottlenecks and improving responsiveness. This approach is highly effective in environments with large datasets and artificial intelligence/machine learning applications, particularly in situations involving IoT, edge computing, and cloud technologies, where centralized structures often face challenges in performance and scalability (Manihar, 2020).

However, implementing Data Mesh comes with notable technical and cultural complexities; it requires substantial organizational change, including a shift toward domain-driven data stewardship and cross-functional collaboration. For smaller enterprises with limited resources, the steep learning curve and infrastructure demands make adoption challenging (Muvva, 2024).Additionally, managing governance and compliance in a decentralized environment can be difficult, particularly for organizations transitioning from deeply entrenched centralized systems. While Data Mesh represents a forward looking solution for scalable, agile data management, its complexity and resource intensity may limit its feasibility for small and medium-sized enterprises (SMEs) in dynamic manufacturing settings such as mechatronics

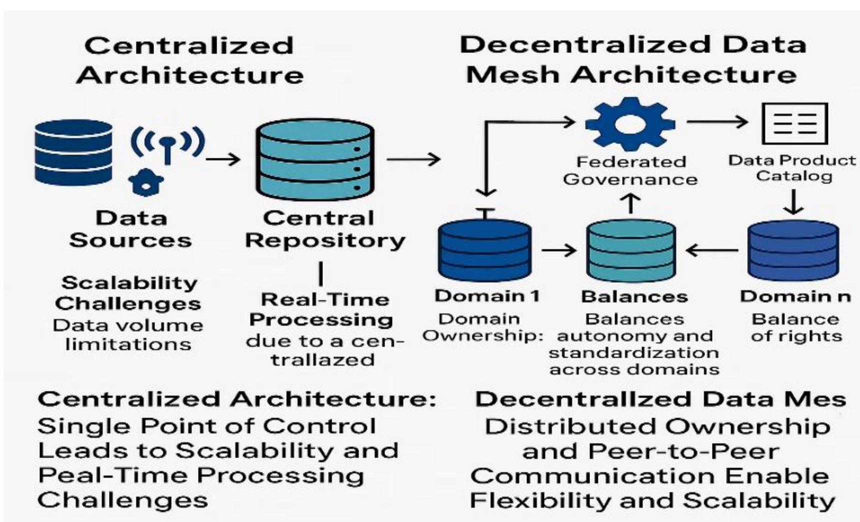

Figure 7. Decentralized structure of Data Mesh compared to traditional centralized architectures.

Source: Author's own elaboration.

This diagram in figure 7 contrasts centralized data architectures where a single hub manages all flows with Data Mesh, where ownership and processing are decentralized across domain specific nodes. The latter approach enhances scalability and supports real-time analytics through federated governance and self-service infrastructure.

Table 7. Comparative Frameworks for Industry 4.0 Adoption in Mechatronics.

FRAMEWORK	STRENGTHS	WEAKNESS/ LIMITATIONS	SUITABILITY FOR MECHATRONICS	REFERENCES/CITATIONS
RAMI 4.0	- Provides standardization and interoperability across diverse industrial systems.	- Generic in nature; lacks explicit mechanisms for real-time processing and AI-KPI integration.	Moderate: Suitable for foundational adoption but insufficient for dynamic manufacturing environments in mechatronics.	(Melo et al., 2021)
	- Comprehensive three-dimensional architecture (layers, lifecycle, hierarchy).	- Abstract nature and insufficient implementation guidelines limit practical applicability	- Rigidity and concerns about data security in cloud manufacturing hinder wider adoption	(Melo et al., 2021)
	- Ensures consistency across industries (manufacturing, supply chain, blockchain-driven projects).	- Struggles with cross-domain integration and high-mix, low-volume production environments.	-Valuable for guiding industry 4.0 adoption but not adaptable to dynamic challenges	(Oñate & Sanz, 2024)
IIRA	- Promotes modularity and flexibility, enabling scalable systems	- Complex to implement; lacks domain-specific guidance and AI-KPI focus.	-Low: Limited applicability due to complexity and lack of focus on mechatronics-specific challenges.	(Pontarolli, 2023)
	- Supports integration of IoT devices and legacy systems.	- High implementation barriers for SMEs due to technical and organizational complexity.	- Does not address real-time processing or predictive analytics critical for dynamic manufacturing environments.	Rocha et al., 2022)
	- Encourages interoperability through standardized interfaces.	- Fails to provide clear guidelines for cross-domain integration in high-mix, low-volume scenarios.	- Better suited for large-scale enterprises with advanced IT capabilities.	(Cavalieri & Salafia, 2020)

Data Pipeline Architectures	- Effective in managing large datasets and supporting data-driven workflows.	-Lacks across domain integration capabilities	-Moderate : Unsuitable for environments requiring seamless interaction between diverse systems	(Budach, 2022)
	- Facilitates centralized data management and analysis.	-Struggles with scalability and flexibility in dynamic manufacturing environments	- Limited ability to handle real-time data processing and AI-driven decision-making.	(Xu et al, 2022)
	- Supports structured data flows and batch processing.	- Inadequate for high-speed, real-time applications common in mechatronics.	- Best suited for static, large-scale data management rather than agile, decentralized environments.	(Peres et al., 2020)
SOA (Service-Oriented Architecture)	- Promotes modularity, flexibility, and reusability through standardized interfaces.	- Struggles with real-time processing and predictive analytics.	Moderate: Valuable for integrating systems but inadequate for dynamic decision-making in high-speed environments.	(Pereyra, 2013)
	- Enables loose coupling and interoperability between services	- Growing system complexity limits adaptability to high-mix, low-volume production environments.	- Limited scalability and inability to address cross-domain challenges in mechatronics.	(Aladwan, 2018)
	- Facilitates modular updates and maintenance.	-Real time analytics and AI-KPI integration are not natively supported	- Suitable for traditional manufacturing but less effective in dynamic, AI-driven scenarios.	(Niemann, 2008)
Data Mesh	- Offers scalability and flexibility, particularly suited for large-scale operations.	- Introduces significant complexity and resource demands, making it less accessible for SMEs.	-High for large-scale operations: Requires domain-specific adaptations for mechatronics.	(Kumara et al., 2024)
	- Decentralized governance addresses security and scalability concerns	-implementation challenges for organizations with deeply entrenched centralized systems	- Superior cross-domain integration but requires careful adaptation to address high-mix, low-volume production	(Manihar, 2020)

	-Supports agile, decentralized data management and self - service infrastructure	- Complexity may deter smaller organizations, especially in dynamic manufacturing environments.	- Ideal for large enterprises but less feasible for SMEs in mechatronics.	(Manihar, 2020)

Source : Adapted from Aladwan et al., (2018,p19) ; Cavalieri and Salafia, (2020,p7); Franco Pereyra et al., (2013,p345); Manihar, (2020,p362); Xu et al, (2022,p10); Melo et al., (2021,p2).

1.6.5. Critical Analysis: Evaluating Frameworks for Industry 4.0 Adoption in Mechatronic

The frameworks reviewed by RAMI 4.0, IIRA, Data Pipeline Architectures, SOA, and Data Mesh each offer distinct strengths but face notable limitations in addressing the challenges of Industry 4.0 adoption in mechatronics. RAMI 4.0 provides a structured, standardized approach that ensures consistency across industries but struggles with real time processing and AI-KPI integration, limiting its adaptability to dynamic manufacturing environments. Similarly, IIRA promotes modularity and flexibility, enabling scalable systems, but lacks domain specific guidance and is complex to implement, making it less suitable for SMEs . Data Pipeline Architectures excel in managing large datasets and supporting data-driven workflows but fail to address cross-domain integration, rendering them unsuitable for dynamic manufacturing scenarios. Meanwhile, SOA promotes modularity and flexibility through standardized interfaces but struggles with real-time analytics and growing system complexity, which limits its applicability in high-mix, low-volume environments. Finally, Data Mesh offers superior scalability and flexibility, particularly for large scale operations, but introduces significant complexity and resource demands, making it less accessible for SMEs .

While each framework has its merits, none fully addresses the unique challenges of mechatronics, such as cross-domain integration, real-time processing, and AI-KPI integration. These gaps highlight the need for domain-specific architectures that bridge the divide between theoretical AI capabilities and practical KPI implementation in mechatronics, particularly in high-mix, low-volume production environments.

1.7. Challenges and Gaps in Current Approaches to AI-KPI Integration in Mechatronics

The integration of Artificial Intelligence (AI) into Key Performance Indicator (KPI) management holds immense potential for optimizing manufacturing processes. However, several challenges hinder its effective implementation, particularly in the mechatronics industry. This section assesses significant challenges, such as scalability issues for small and medium enterprises (SMEs), limited real-time processing capabilities, data integration fragmentation, inadequate focus on sustainability metrics, and unique challenges specific to mechatronics. By addressing these gaps, manufacturers can unlock the full potential of AI-driven KPI systems.

1.6.6. Scalability Challenges for SMEs

Small and Medium Enterprises (SMEs) encounter major obstacles when trying to implement AI-driven Key Performance Indicator (KPI) frameworks in mechatronics. These include limited financial resources, lack of technical expertise , high initial costs , and integration difficulties with legacy systems all of which hinder scalability and adoption in dynamic, high-mix, low-volume production environments typical of mechatronics (Martínez-Arellano & Ratchev, 2024).

A key challenge is data availability and quality . AI models require large volumes of high-quality data to produce accurate insights. However, SMEs often struggle with inconsistent data collection, limited historical datasets, and concept drift due to frequent changes in manufacturing processes (Zavodna, Überwimmer, & Frankus, 2024). Additionally, the cost of developing, deploying, and maintaining AI systems can consume up to 30% of an SME's IT budget , limiting room for scaling (Rane, Kaya, & Rane, 2024).

Many SMEs also lack in-house expertise in machine learning, data science, and system integration, making implementation complex and time-consuming (Oldemeyer, Jeon, & Teuteberg, 2024). Furthermore, legacy system compatibility creates technical debt, as retrofitting outdated infrastructure for AI integration can be costly and technically demanding (Proietti & Magnani, 2025). Regulatory concerns such as data privacy , security , and responsible AI use further delay deployment by adding compliance layers(Yusuf, Pervin, & Román-González, 2024).

Despite these challenges, several scalable solutions have been proposed:

- Frugal Industrial AI , focusing on data efficient models using existing knowledge bases.
- AI as a Service (AIaaS) , offering cloud-based AI tools via subscription models.
- Phased adoption strategies, starting with general-purpose AI tools before progressing to domain-specific ones.
- Workflow optimization systems , leveraging predictive analytics for operational efficiency.
- Industry-specific AI platforms , tailored to address niche requirements of SMEs.

However, many current approaches are designed for large enterprises and fail to account for SME specific needs. There remains a gap in interdisciplinary research , regional adaptability , and sustainability considerations in AI-KPI integration efforts (Espina-Romero, 2024).

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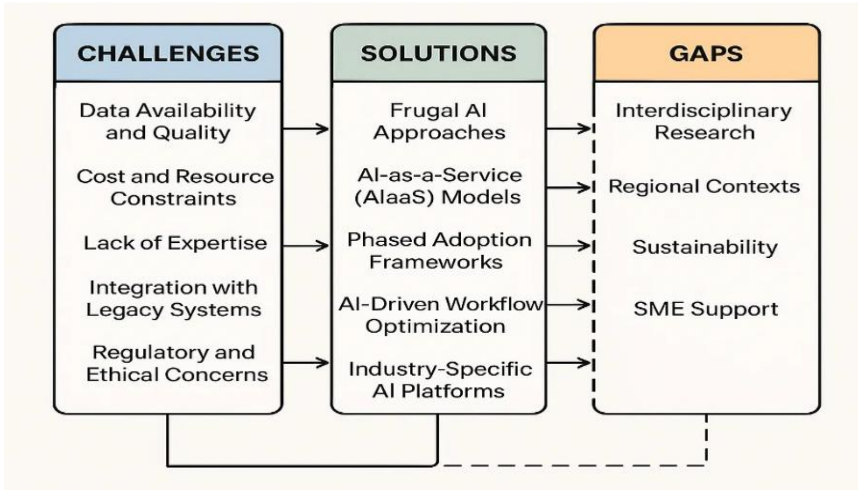

Figure 8. Flowchart of Scalability Challenges, Solutions, and Gaps in AI-KPI Integration for SMEs.

Source: Author's own elaboration.

1.7.1. Limited Real-Time Processing Capabilities

Real-time processing the ability to analyze and respond to data as it is generated is essential for timely decision-making in manufacturing applications such as predictive maintenance, quality control, and anomaly detection. However, limited real-time capabilities pose significant challenges, particularly in resource constrained mechatronic systems where edge devices often lack the computational power, memory, or energy capacity to support complex AI models (Jain, Wadhwani, & Eastman, 2023). Transmitting data to the cloud introduces latency, which can compromise performance in time-sensitive operations like industrial automation or autonomous systems .

Edge AI offers a promising solution by enabling local data processing, but its implementation is hindered by hardware limitations and energy constraints, especially for battery-powered IoT devices (Campolo, Genovese, Iera, & Molinaro, 2021). Security and privacy concerns further complicate AI-KPI integration, as sensitive data must be protected from unauthorized access.

While approaches like lightweight models, hybrid edge cloud architectures, federated learning, and hardware accelerators have shown potential, key gaps remain particularly regarding integration with legacy systems, reliance on high-quality data, and ensuring consistent performance across heterogeneous environments (Yang, Hu, and Chen (2023). Addressing these will require scalable architectures, improved efficiency-accuracy trade-offs, secure federated learning protocols, and energy-efficient computing solutions.

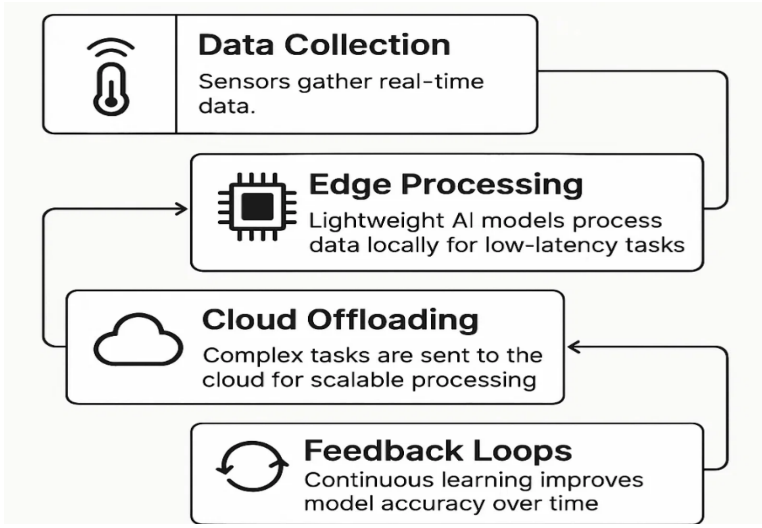

Figure 9. Workflow of AI-Driven Real-Time Processing in Mechatronics.

Source: Author's own elaboration.

1.7.2. Fragmentation in Data Integration

The integration of Artificial Intelligence (AI) with Key Performance Indicators (KPIs) in mechatronics faces significant challenges, primarily due to data fragmentation . This results from a variety of data sources, formats, and platforms, making it challenging to develop unified AI systems (Salamkar, 2023; Windmann, Wittenberg, Schieseck, & Niggemann, 2024). Inconsistent semantics further hinder integration, as similar data from different sources often lacks alignment, leading to mapping difficulties . Moreover, uncertain data integration can lead to inaccurate outcomes, undermining system dependability (Magnani & Montesi, 2007).

Beyond fragmentation, technical and methodological gaps limit progress. AI-driven integration tools struggle with schema matching, conflict resolution, and managing the scale of mechatronic data (Salamkar, 2023).Real-time integration remains a challenge, as delays can compromise responsiveness in time-sensitive environments .Data quality and governance are equally critical, with concerns around volume, privacy, and security requiring robust management.

Organizationally, aligning AI capabilities with strategic goals and ensuring system trustworthiness remain essential yet difficult tasks (Windmann et al., 2024).

Despite these hurdles, ongoing advancements in AI-driven integration tools , automated frameworks , and data quality techniques offer promising solutions. However, continuous refinement is needed to address evolving system complexity and ensure measurable performance improvements in AI-KPI integration.

Table 8. Common Data Integration Challenges in Mechatronics.

CHALLENGE	DESCRIPTION	IMPACT	SOURCES
Diverse Data Sources	Fragmented data landscape due to sensors, cyber-physical systems, and platforms..	Complicates integration across formats and platforms.	Salamkar,S. 2023;
Semantic Ambiguity	Data from different sources lacks semantic consistency.	Difficulty in mapping and integrating data effectively.	Windmann et al., 2024
Uncertainty in Integration	Inherent uncertainty in data integration processes.	Misleading results, compromised reliability of AI-KPI systems.	Magnani & Montesi, 2007;
Legacy System Compatibility	Outdated systems lack connectivity for modern AI platforms.	Fragmented data streams, integration barriers.	Windmannet al., 2024
Real-Time Processing	Need for efficient data pipelines and processing frameworks.	Latency issues hinder responsiveness and decision-making.	koren et al.,2024

Source: Author's own elaboration.

1.7.3. Insufficient Focus on Sustainability Metrics

Sustainability has become a critical focus in modern manufacturing, driven by regulatory pressures and market demands for greener operations. However, many traditional Key Performance Indicator (KPI) systems fail to effectively track ecological metrics such as energy consumption, carbon emissions, and waste generation, limiting manufacturers ability to align efficiency with environmental goals (Gebara, Thammaraksa, Hauschild, & Laurent, 2024). This gap also applies to AI-driven KPI frameworks, where important tools like Life Cycle Assessment (LCA) for enhancing sustainable production are not fully utilized. The lack of integration not only hampers environmental improvements but also exposes companies to compliance risks and rising operational costs.

The complexity of AI data requirements further complicates sustainability metric integration, especially when addressing data security and privacy concerns. Moreover, interdisciplinary approaches that combine AI with domain expertise in sustainability are underexplored, despite their potential to enhance decision-making (Gautam, Khan, Gani, & Asjad, 2024).While some AI-based KPI frameworks prioritize operational efficiency, they often neglect environmental and social dimensions, resulting in an imbalanced view of performance .To address this disparity, AI-KPI systems need to progress by integrating comprehensive sustainability indicators. This requires better data utilization, stronger interdisciplinary collaboration, and ethical considerations in AI deployment ; by integrating ecological KPIs into AI systems, manufacturers can improve both environmental performance and long-term business resilience, aligning industrial growth with global sustainability targets (Schoormann et al.,2023)

Table 9. Common Sustainability Metrics.

METRIC	DEFINITION	BENEFITS	SOURCES
Energy Consumption	Amount of energy used in production	Reduces operational costs	Milewska and Milewski (2023)
Carbon Emissions	Volume of greenhouse gases emitted	Aligns with regulatory compliance	Padgett, Steinemann, Clarke, and Vandenbergh (2008)
Waste Generation	Quantity of waste produced during production	Improves resource efficiency	Beigl, Lebersorger, and Salhofer (2008)

Source: Author's own elaboration based on Beigl, Lebersorger, and Salhofer (2008); Padgett, Steinemann, Clarke, and Vandenbergh (2008); Milewska and Milewski (2023).

1.8. Theoretical Foundations and Comparative Analysis for AI-Driven KPI Systems in Mechatronics

The integration of Artificial Intelligence (AI) into Key Performance Indicator (KPI) management is revolutionizing manufacturing by addressing inefficiencies, enabling smarter decision-making, and aligning operational excellence with sustainability goals. This explores the theoretical foundations guiding AI-driven KPI systems, evaluates their strengths and limitations, and provides a comparative analysis of traditional KPI systems versus AI-driven alternatives. Additionally, it examines validation methods to ensure the reliability and applicability of theoretical frameworks in dynamic manufacturing environments, particularly in the mechatronics industry.

1.8.1. Theoretical Foundations Guiding AI-Driven KPI Systems

1.8.1.1. Socio-Technical Systems Theory

Socio-Technical Systems (STS) Theory emphasizes the interdependence between social and technical components within organizations, offering a foundational framework for integrating AI-driven Key Performance Indicator (KPI) systems into complex environments . Originating from the Tavistock Institute, STS theory advocates for joint optimization balancing human and technological elements to enhance organizational performance (Appelbaum, 1997).

In AI-KPI integration, STS supports the development of systems that augment human capabilities , rather than replace them. It highlights the importance of aligning AI tools with organizational culture , user interfaces , and ergonomic design , ensuring that technology adoption enhances both productivity and employee well-being (Viskova-Robertson,2023; Yeazitzis et al.,2023).This approach promotes continuous adaptation and emergent behavior, making it particularly relevant in dynamic industrial settings like mechatronics.

However, applying STS theory in modern AI systems presents challenges. Its concepts are often difficult to operationalize in complex adaptive environments, and traditional STS models may not fully capture the rapid evolution of intelligent technologies (López-Chau, Rojas-Hernández, Valle-Cruz, & Trujillo-Mora, 2023). Recent advancements, like intelligent Socio-Technical Systems (iSTS), combine AI principles focused on humans to fill these gaps and enhance decision-making based on data.

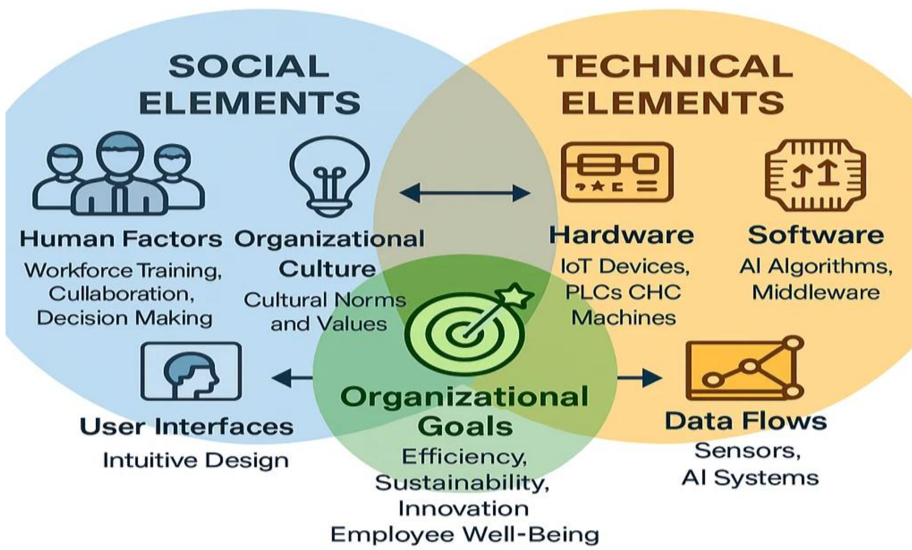

Figure 10. Interplay Between Social and Technical Elements in AI-Driven KPI Systems.

Source: Author's own elaboration.

This figure 10 illustrates the socio-technical systems framework applied to AI-driven KPI integration. It shows the interdependence between social elements (human factors, organizational culture, and user interfaces) and technical elements (hardware, software, and data flows), with organizational goals at the center guiding the alignment process.

1.8.1.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) serves as a widely recognized model for understanding how users accept and adopt new technologies. It identifies four key constructs:

-Performance Expectancy

-Effort Expectancy

-Social Influence

-Facilitating Conditions

These factors influence user behavior and intention across various domains, including healthcare, education, and business .In AI-driven KPI systems, UTAUT helps explain how employees interact with and accept AI-based tools, especially in industrial environments where change resistance can hinder implementation success. Extensions to the model such as perceived organizational support have improved its relevance by highlighting how institutional backing influences adoption behaviors (Dwivedi, Rana, Tamilmani, & Raman, 2020). Despite its utility, UTAUT has limitations. Critics argue that its construct set is too narrow to fully represent the complexity of technology acceptance, especially in diverse cultural or organizational contexts (Dwivedi et al.,2020).Additionally, overreliance on UTAUT may stifle innovation in acceptance modeling, reducing the exploration of alternative frameworks (Blut & Chong, 2022).

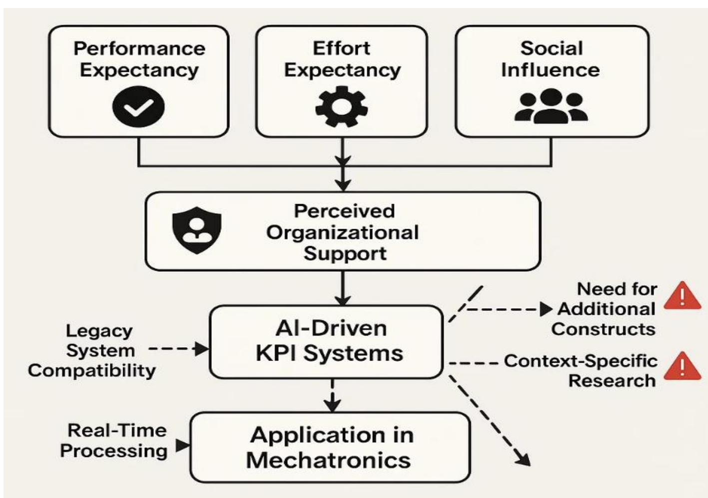

Figure 11. Conceptual Diagram of UTAUT Framework in AI-KPI Systems Integration.

Source: Author's own elaboration.

This figure 11 illustrates the UTAUT framework and its application in AI-KPI systems integration. It shows the core constructs of UTAUT, extensions like perceived organizational support, and the challenges faced in applying UTAUT to mechatronics, such as legacy system compatibility and real-time processing requirements.

1.8.1.3. Econometric Modeling

Econometric modeling provides a structured methodology for analyzing economic indicators and forecasting trends, playing a crucial role in setting and evaluating KPIs related to market dynamics, resource allocation, and strategic planning (Charpentier, 2018). In AI-driven KPI systems, econometric approaches help organizations quantify the impact of AI on metrics like productivity , cost reduction , and market responsiveness .

AI enhances traditional econometric methods by processing large volumes of heterogeneous data and identifying non-linear patterns, enabling more accurate predictions and strategic alignment (Wang & Aviles, 2023). For example, AI can refine KPIs derived from demand-supply models, rational choice theory, and game theory, improving insights into consumer behavior and competitive positioning (Nyathani,2023).Moreover, AI-driven KPI systems offer real-time feedback and personalized performance tracking, supporting objective evaluations and tailored improvement strategies. These systems standardize data inputs from multiple sources, enhancing consistency and reliability in performance measurement. Nevertheless, deploying AI in econometric KPI systems introduces challenges. Model complexity and calibration requirements can limit practical applicability, while issues like algorithmic bias and data privacy concerns raise ethical questions .Ensuring transparency and fairness in AI-enhanced KPI frameworks remains critical to maintaining trust and compliance.

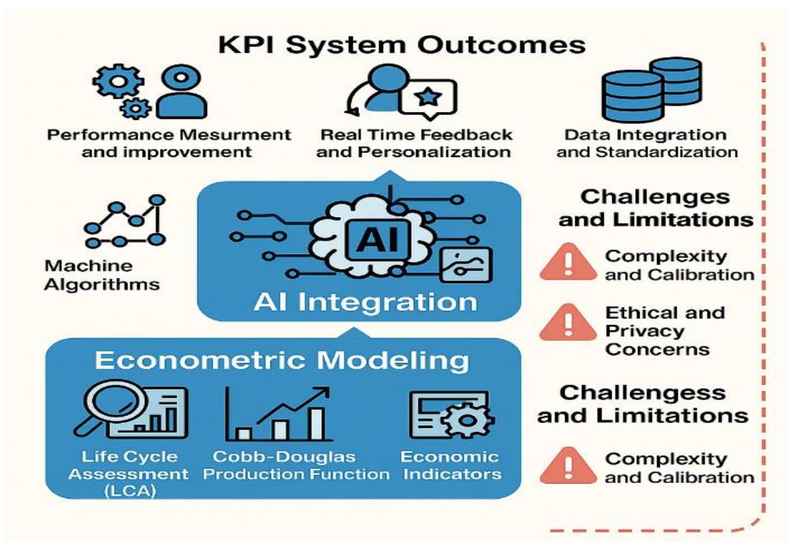

Figure 12. Integration of Econometric Modeling and AI in KPI Systems.

Source: Author's own elaboration.

This figure 12 illustrates the integration of econometric modeling and AI in KPI systems, showing how AI enhances econometric approaches to improve performance measurement, real-time feedback, and data standardization. It also highlights key challenges such as model complexity, calibration, and ethical considerations.

1.8.2. Comparative Analysis: Traditional KPI Systems vs. AI-Driven KPI Systems

AI-driven Key Performance Indicator (KPI) systems offer significant advantages over traditional KPI frameworks in terms of data processing speed , accuracy , scalability , and sustainability integration . Unlike traditional KPI systems, which rely on historical data and manual analysis, AI-driven models leverage machine learning and predictive analytics to process vast datasets in real-time, enabling proactive decision-making and operational agility .This shift from reactive to predictive insights allows organizations to anticipate equipment failures, respond swiftly to market dynamics, and maintain a competitive edge (Badmus,2024). Additionally, AI-enhanced systems reduce human error by automating data interpretation and offering customized solutions tailored to specific business needs, improving both the precision and relevance of performance metrics.

From a sustainability perspective , AI-driven KPI systems outperform traditional approaches by optimizing resource use and minimizing waste through advanced data modeling particularly beneficial in sectors like manufacturing and supply chain management (Cihan, 2023).These systems also support real-time capabilities , reducing inefficiencies and lowering long-term costs compared to conventional methods that often result in delayed decisions and higher operational expenses (Wang & Aviles, 2023). Moreover, AI's ability to manage multi-source, heterogeneous datasets enables scalable implementation across both SMEs and large enterprises, while modular architectures allow for flexible adaptation to evolving business requirements .

Despite these benefits, adopting AI-driven KPI systems presents challenges: resistance to change, lack of technical expertise, and high initial investment can hinder user adoption and implementation (Dumas et al., 2022; Yesufu & Alajlani, 2025). However, when successfully integrated, AI not only enhances cost efficiency and innovation through technologies such as digital twins, IoT, and machine learning but also supports more strategic and sustainable business practices.

- **Critical evaluation**

While AI-driven KPI systems offer significant advantages over traditional systems, they also present challenges that must be addressed to maximize their potential. Ethical concerns, such as algorithmic bias and data privacy, require careful management to maintain credibility and trust . The reliance on high-quality data and robust validation methods, such as continuous feedback mechanisms and simulation-based testing, is critical to ensuring accuracy and reliability . Additionally, the complexity of AI systems can hinder user adoption, necessitating intuitive interfaces, comprehensive training programs, and frameworks like UTAUT to guide acceptance . Interdisciplinary collaboration between fields such as computer science, industrial engineering, and electrical engineering is essential to address challenges related to data quality, scalability, and interpretability . Despite these challenges, AI-driven systems provide unmatched capabilities in real-time data processing, sustainability integration, error reduction, and scalability, making them indispensable for modern, data-driven business environments.

1.9. Validation Methods for Theoretical Frameworks

Validation methods for theoretical frameworks and simulation-based models are crucial for ensuring that models are accurate, reliable, and applicable in fields like computer science, industrial engineering, and electrical engineering. Key methods include Discrete Event Simulation (DES), which models systems with stochastic elements and validates outcomes through techniques like animation and statistical testing (Sargent, 1999). Monte Carlo Simulation, which uses random sampling to quantify uncertainty and assess model robustness (Sargent, 2011) ; and System Dynamics Modeling, which evaluates long-term system behavior using stock-and-flow diagrams and sensitivity analysis. AI-driven KPI systems leverage machine learning algorithms to optimize operational efficiency, with validation relying on metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Precision, Recall, and F1-score (Sargent, 2011). Uncertainty evaluation is critical, employing techniques like Monte Carlo sampling and probability bounds analysis to address aleatory and epistemic uncertainties. Synthetic datasets and empirical data play complementary roles in validation, particularly when real-world data is scarce or restricted (Law,2009).Ensuring validity and reliability involves cross-validation, sensitivity analysis, and robust testing under diverse scenarios. Interdisciplinary collaboration is vital to integrate expertise from various fields, addressing challenges like data quality, scalability, and interpretability (Sargent, 2011). Proprietary industrial data enhances real world applicability but raises concerns about privacy and access restrictions .

- **Critical evaluation**

While the discussed validation methods provide robust tools for assessing AI-driven KPI systems and simulation models, their effectiveness depends on careful implementation and interdisciplinary collaboration. Techniques like DES, Monte Carlo Simulation, and System Dynamics Modeling offer valuable insights but often rely on synthetic datasets, which may limit real-world applicability unless complemented by empirical data . Challenges such as data quality, scalability, and interpretability remain significant barriers, particularly in complex, large scale systems where poor quality data can undermine model credibility. Additionally, the black box nature of AI models and the dynamic behavior of systems pose unique validation challenges, necessitating advanced techniques like explainable AI and probabilistic verification . Ethical considerations, such as algorithmic bias and data privacy, must also be addressed to ensure trustworthiness and accountability.

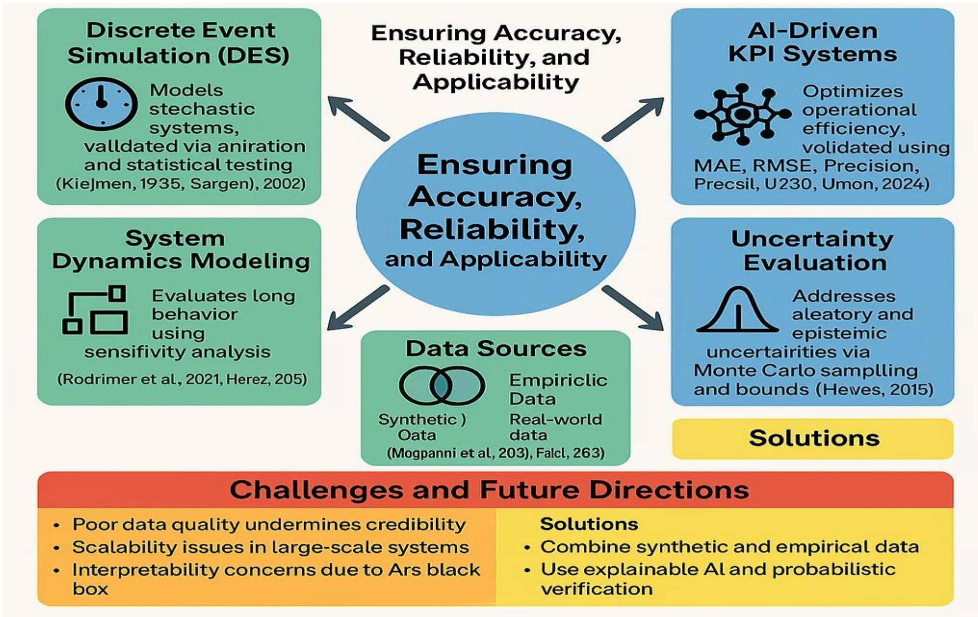

Figure 13. Validation Methods for Theoretical Frameworks and AI-Driven KPI Systems.

Source: Author's own elaboration.

1.10. Identification of Research Gaps in AI-Driven KPI Integration for Mechatronics

The integration of AI-driven Key Performance Indicators (KPIs) in the mechatronics industry is constrained by several critical research gaps that hinder operational efficiency and innovation, while also presenting transformative opportunities if addressed effectively. A significant challenge is the limited integration of theoretical AI advancements with practical implementation, as machine learning and predictive analytics often fail to translate into real-world applications due to issues like legacy system compatibility and adapting to dynamic manufacturing environments (Palhares, Novelli, & Morelli, 2020.)Bridging this gap requires robust methodologies, such as hybrid systems or domain-specific frameworks, to align AI models with existing infrastructure and operational demands. Additionally, Industry 4.0 frameworks lack tailored architectures for the unique requirements of mechatronics, such as high-mix, low-volume production and cross-domain integration, limiting AI's ability to enhance interoperability and scalability in smart factories(Liagkou,2021).Developing flexible, domain specific solutions is essential to address these complexities effectively. Another pressing issue is the absence of validated frameworks connecting AI techniques to specific KPI objectives, resulting in suboptimal implementations that fail to deliver measurable improvements in operational efficiency or sustainability metrics (Ajemba & Arene, 2022).

Interdisciplinary collaboration is crucial to create standardized yet adaptable frameworks that ensure alignment with organizational goals. Furthermore, traditional KPI systems struggle with real-time processing capabilities, impeding predictive maintenance and responsiveness to dynamic production changes . Advanced AI techniques, such as digital twins and IoT platforms, offer potential solutions but require overcoming technical challenges like data latency and system compatibility. Broader challenges, including poor data quality, legacy system compatibility, and interoperability, further complicate AI integration (Kovalenko, Barton, Moyne, & Tilbury, 2023). Addressing these gaps through interdisciplinary research and collaboration is vital to unlocking AI's full potential, enabling seamless adoption in modern manufacturing environments, and driving operational efficiency and innovation in the mechatronics industry. By fostering partnerships between academia, industry, and government, stakeholders can develop adaptive solutions that resolve these barriers and fully realize AI's transformative capabilities in mechatronics.

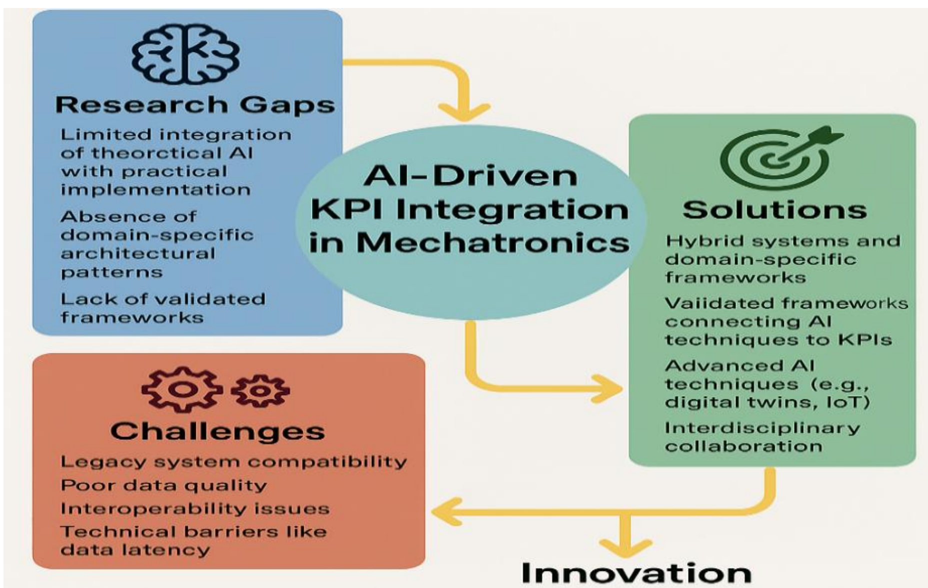

Figure 14. AI-Driven KPI Integration in Mechatronics.

Source: Author's own elaboration.

1.11. Comprehensive Framework for AI-Driven KPI Management in the Mechatronics Industry

The integration of Artificial Intelligence (AI) into Key Performance Indicator (KPI) management represents a transformative advancement for manufacturing, particularly in the mechatronics industry. This presents a comprehensive framework tailored specifically for mechatronics, addressing inefficiencies in traditional KPI systems and leveraging advanced AI techniques such as predictive analytics, real-time decision-making, and sustainability metrics. By comparing this framework with existing solutions, evaluating its strengths and weaknesses, and analyzing its potential impact, this report highlights its novelty, practical applicability, and alignment with emerging Industry 4.0 trends.

1.11.1. Comprehensive Explanation of the Framework

The proposed framework represents a transformative approach to Key Performance Indicator (KPI) management in the mechatronics industry by integrating Artificial Intelligence (AI) with IoT , machine learning , and digital twin technologies to overcome limitations of traditional systems. It shifts from reactive to proactive operations through predictive maintenance , where models such as Gradient Boosting and Random Forest are used to forecast equipment failures and optimize maintenance schedules (Li, Wei, & He, 2018). By accurately predicting the Remaining Useful Life (RUL) of industrial assets, the framework minimizes unplanned downtime and enhances resource allocation .In parallel, it supports real-time decision-making by leveraging IoT sensors and digital twins for continuous data acquisition and dynamic model training (Mahdi,2022).The use of Explainable AI (XAI) ensures transparency in AI-driven decisions, fostering stakeholder trust and enabling rapid, informed responses to operational anomalies .

The framework also embeds ecological KPIs to align manufacturing practices with sustainability goals, addressing a major gap in current AI-driven systems (Sherif et al., 2022) .By integrating Life Cycle Assessment (LCA) tools , it enables manufacturers to evaluate environmental impacts across product life cycles, promoting greener production methods, reducing waste, and supporting regulatory compliance (Barni, 2022). To ensure broad applicability across industries, the framework is designed with scalability and adaptability in mind. Its modular architecture allows seamless integration with legacy systems and accommodates diverse hardware-software configurations, making it suitable for both large enterprises and SMEs with limited technical resources (Harun, 2019).Data from IoT devices, ERP/MES platforms, and LCA tools is aggregated into a unified pipeline, where advanced analytics extract actionable insights displayed via intuitive dashboards to support agile, data-driven decision-making.

1.12. Differentiation from Existing Frameworks

To highlight the novelty and practical applicability of the proposed AI-driven KPI framework for mechatronics, it is essential to differentiate it from established reference models such as RAMI 4.0 , IIRA , and Data Mesh . While these frameworks provide valuable foundations for Industry 4.0 adoption offering standardization (RAMI 4.0), modularity (IIRA), and decentralized data governance (Data Mesh) they fall short in addressing key requirements of dynamic manufacturing environments, particularly those involving real-time decision-making,AI-KPI integration,and domain-specific customization (Pontarolli, 2023; (Wider, Verma, & Akhtar, 2023).Unlike RAMI 4.0 , which lacks explicit mechanisms for integrating AI into KPI systems and real-time analytics, the proposed framework enhances responsiveness through

IoT-enabled sensor data processing and predictive modeling . Similarly, while IIRA supports modular system design, it offers limited guidance on handling high-mix, low-volume production environments typical of mechatronics. The proposed framework addresses this by offering explicit recommendations for AI technique selection , enabling tailored deployment that aligns with industry-specific needs (Rocha et al;, 2022). Furthermore, compared to Data Mesh , which excels in scalability but introduces complexity that may overwhelm SMEs, the proposed model balances centralized and decentralized approaches to ensure accessibility without compromising performance. This hybrid structure supports seamless data flow and robust analytics across organizations of all sizes.

The framework's strengths lie in its ability to enhance operational efficiency , reduce unplanned downtime , and embed ecological KPIs using Life Cycle Assessment (LCA) tools. It also leverages Explainable AI (XAI) to generate transparent insights via intuitive dashboards, improving stakeholder trust and decision-making. However, challenges remain, particularly concerning data quality , availability , and the need for further validation in domain-specific contexts. Ongoing efforts focus on developing resilient data management strategies and AI algorithms capable of handling incomplete or noisy data to improve reliability and adaptability.

1.13. Potential Impact and Future Relevance

The proposed AI-driven KPI framework has significant strategic implications for the mechatronics industry by addressing core operational, environmental, and technological challenges while aligning with Industry 4.0 trends. It enhances operational efficiency by reducing unplanned downtime by up to 40% through predictive maintenance strategies, optimizing resource allocation, and improving productivity key outcomes that support lean manufacturing principles .From a sustainability perspective , the framework enables manufacturers to embed ecological KPIs such as carbon footprint and waste generation using Life Cycle Assessment (LCA) tools, helping them comply with global sustainability goals and reduce environmental impact through data-driven resource optimization . This integration supports companies in transitioning toward greener production models without compromising economic performance. In terms of real-time decision-making , the framework leverages IoT sensors and machine learning to process live data streams, enabling swift responses to anomalies and dynamic market shifts. By incorporating explainable AI (XAI), it also fosters stakeholder trust and transparency in automated decisions. Furthermore, the framework demonstrates strong alignment with emerging Industry 4.0 technologies including digital twins, edge computing, and federated learning ensuring adaptability and relevance in evolving industrial environments . Notably, its modular design ensures accessibility for small and medium enterprises (SMEs) , which often face barriers like high implementation costs and limited technical expertise. By offering scalable deployment options, the framework empowers SMEs to achieve cost savings, improve competitiveness, and adopt advanced analytics without requiring large upfront investments.

1.14. Roadmap for Implementation

The roadmap for implementing the proposed framework includes the following steps:

1. Methodologies :Combine physics-based simulations with machine learning to improve prediction accuracy, particularly in scenarios with limited historical data.
2. Datasets :Develop synthetic datasets reflecting real-world scenarios, validated using Python-based simulations.
3. Tools : Integrate LCA tools to embed ecological KPIs and align with global sustainability trends.
4. Validation Process : Use metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Precision, Recall, and F1-Score to evaluate performance.

The roadmap ensures a systematic approach to implementation, addressing challenges related to data quality, validation, and domain-specific needs.

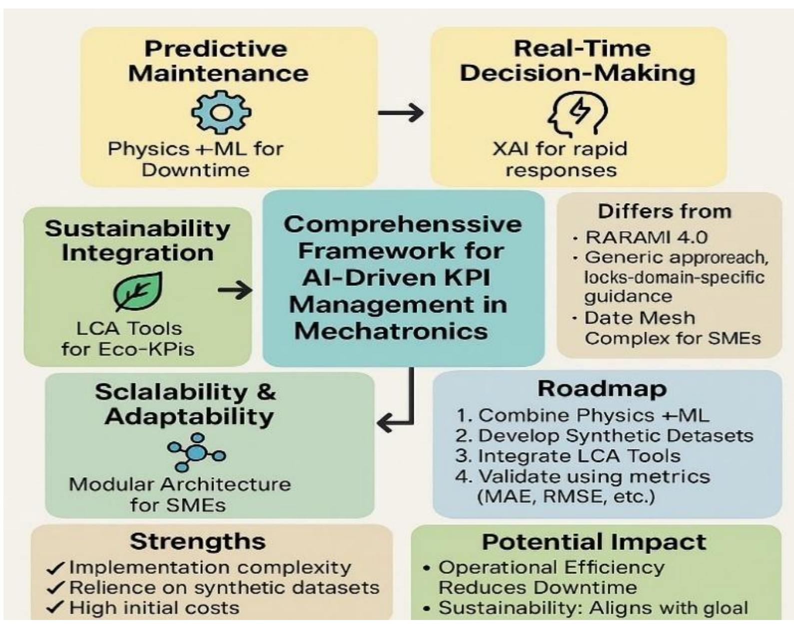

Figure 15. Comprehensive Framework for AI-Driven KPI Management in Mechatronics.

Source: Author's own elaboration.

1.15. Conclusion

The proposed AI-driven KPI management framework represents a transformative advancement for the mechatronics industry. By addressing inefficiencies in traditional KPI systems and leveraging advanced AI techniques, it enhances operational efficiency, promotes sustainability, and supports real-time decision-making. While challenges such as implementation complexity and high initial costs remain, the framework’s scalability and adaptability make it suitable for organizations of all sizes. As these technologies mature, they are poised to revolutionize manufacturing by promoting automation, sustainability, and competitiveness, paving the way for a smarter, more resilient industrial ecosystem.

2. Methodology

2.1. Research Design

The research design is structured to address the core objectives of this study by aligning with three key research questions:

1. How can AI techniques improve KPI management efficiency in the mechatronics industry?

This question explores the role of machine learning algorithms (e.g., regression models, neural networks) in optimizing operational efficiency. The focus is on early anomaly detection to enable proactive measures that maintain maximum efficiency.

2. What are the challenges in implementing AI-driven KPI systems, particularly in complex mechatronics environments?

This question investigates barriers such as data quality, scalability, interpretability, legacy system compatibility, and adaptation to dynamic manufacturing conditions.

3. How can ecological KPIs be integrated into traditional frameworks to promote sustainable manufacturing practices?

This question focuses on embedding sustainability metrics (e.g., energy consumption, carbon footprint) into AI-driven KPI systems to measure the benefits of combining business and environmental KPIs.

These research questions are supported by the following hypotheses:

H1 : AI-driven KPI systems improve operational efficiency, quality, and productivity by providing accurate and timely insights.

H2 : Predictive analytics and machine learning models in KPI systems facilitate better real-time decision-making.

H3 : Incorporating ecological KPIs through Life Cycle Assessments (LCA) in the AI-enhanced framework contributes to more sustainable manufacturing practices.

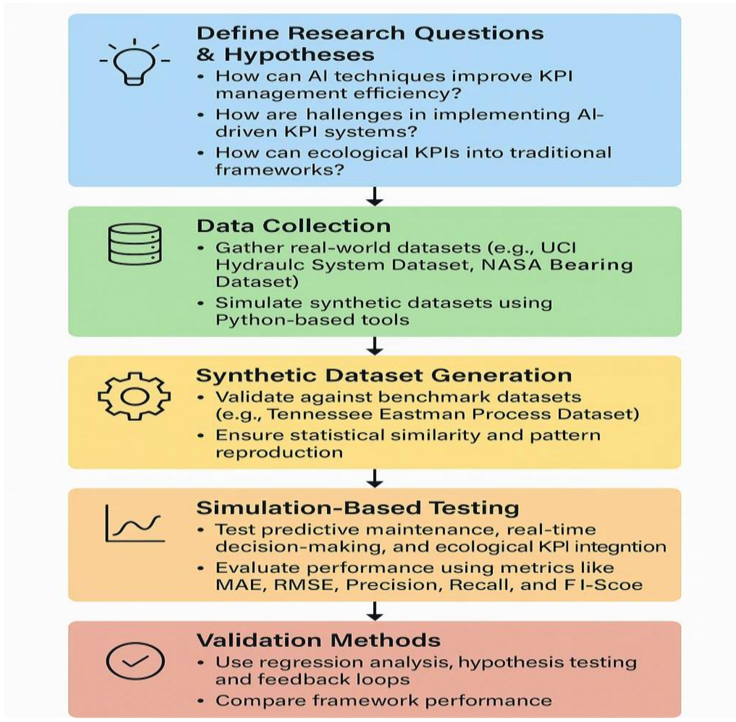

Figure 16. Research Design Workflow.

Source: Author's own elaboration.

This figure illustrates the logical progression of the research process, from defining research questions to validation methods, ensuring alignment between objectives, methodologies, and outcomes.

2.2. Objective of the Study and Research Hypotheses

The primary objective of this study is to develop a functional architecture that integrates artificial intelligence (AI) techniques to enhance key performance indicator (KPI) management and improve production performance within the mechatronics industry. The research aims to address inefficiencies in traditional systems by leveraging advanced technologies such as the Internet of Things (IoT), machine learning, and digital twins. These technologies are designed to optimize operational efficiency, promote sustainability, and ensure real-time decision-making capabilities. To achieve this objective, the study is guided by three hypotheses:

The first hypothesis (H1) posits that AI-driven KPI management frameworks lead to improved operational efficiency, quality, and productivity. This hypothesis will be validated through regression analysis using data collected from IoT sensors that track machine performance and productivity metrics. The second hypothesis (H2) suggests that predictive analytics and machine learning models in KPI systems facilitate better real-time decision-making. This hypothesis will be tested using time-series analysis and neural networks applied to production data obtained from enterprise resource planning (ERP) and manufacturing execution systems (MES). The third hypothesis (H3) proposes that incorporating ecological KPIs through Life Cycle Assessments (LCA) in the AI-enhanced framework contributes to more sustainable manufacturing practices. Econometric models, such as the Cobb-Douglas production function, will be used to analyze the influence of green manufacturing practices on production performance and sustainability. This structured approach ensures alignment between objectives, methodologies, and expected outcomes, providing a logical foundation for the research process.

2.3. Description of Data Collection

Data collection was carried out over a six-month period, from November 2024 to May 2025, to ensure comprehensive coverage of both operational and ecological KPIs. The process focused on gathering data through automated real-time production systems, specifically targeting the validation of each hypothesis.

- IoT Sensors : Collected real-time data on machine uptime, output quality, and energy consumption, which are essential for validating H1 as they reflect the operational performance of machinery.
- ERP Systems : Captured data on throughput, resource allocation, and maintenance logs, which were used to validate H2 by assessing improvements in decision-making and resource optimization.
- MES Systems : Provided real-time production data from the factory floor, vital for evaluating H2 and enhancing decision-making capabilities in production processes.
- LCA Tools : Gather data related to ecological KPIs such as waste generation and energy usage, which were used to validate H3 by assessing the sustainability of production processes.

To complement real-world data, synthetic datasets were generated using Python-based simulations. These datasets ensured comprehensive testing of the AI-driven KPI framework across diverse industrial scenarios.

Python Code for Synthetic Dataset Generation :

Below is an example of Python code used to generate synthetic IoT sensor data for predictive maintenance and anomaly detection:

```
import numpy as np

import pandas as pd

def generate_sensor_data(num_points=1000, anomaly_rate=0.05):
```

```
    Generates synthetic IoT sensor data with configurable parameters.
    """
    time = np.linspace(0, 100, num_points)
    temp = 50 + 10 * np.sin(time / 5) + np.random.normal(0, 2, num_points)
    vibration = 0.5 + 0.1 * np.cos(time / 10) + np.random.normal(0, 0.1, num_points)
    anomalies = np.random.rand(num_points) < anomaly_rate
    temp[anomalies] += np.random.normal(20, 5, anomalies.sum())
    vibration[anomalies] += np.random.normal(0.5, 0.1, anomalies.sum())
    return pd.DataFrame({
        'time': time,
        'temperature': temp,
        'vibration': vibration,
        'is_anomaly': anomalies.astype(int)
    })
# Example Usage
sensor_data = generate_sensor_data()
print(sensor_data.head())
```

This script generates realistic time-series patterns for temperature and vibration, incorporating trends, noise, and anomalies to evaluate detection systems. The adjustable anomaly_rate parameter allows for controlled injection of anomalies, ensuring robust testing of the framework's ability to identify potential equipment failures.

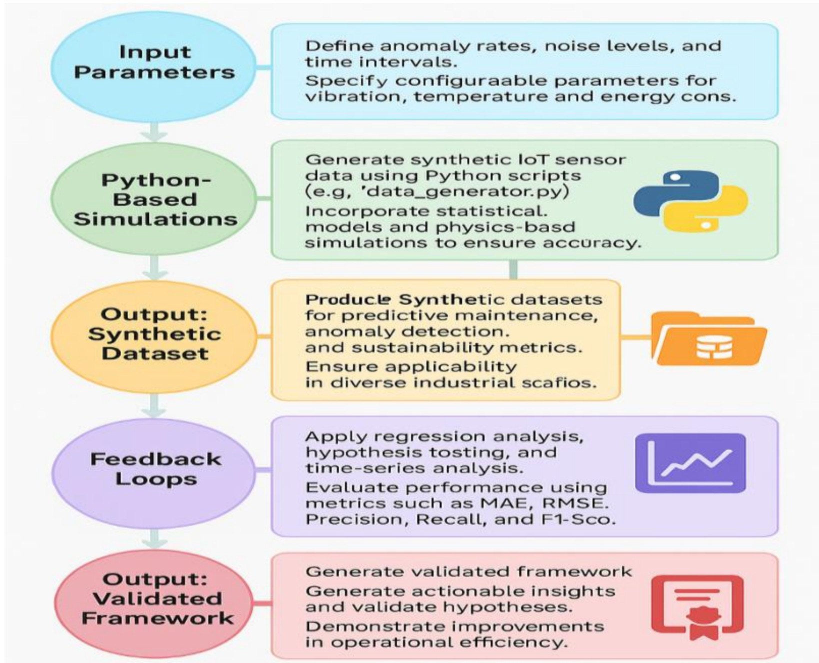

Figure 17. Workflow for Synthetic Dataset Generation and Validation in AI-Driven KPI System.

Source: Author’s own elaboration.

This figure highlights the integration of input parameters, Python-based simulations, and validation mechanisms.

Several challenges arose during data collection, including inconsistencies in sensor readings due to environmental factors and incomplete datasets from ERP systems. Additionally, ensuring compatibility between different data sources required significant preprocessing efforts. Ethical considerations were prioritized throughout the data collection process. Data privacy was maintained by anonymizing sensitive information, and informed consent was obtained from all stakeholders involved in providing production data. Furthermore, the use of synthetic datasets ensured compliance with ethical guidelines while addressing limitations in data availability.

2.4. Description of Data Analysis

All statistical analyses and econometric models were described with sufficient clarity to allow readers to verify the reported results. The data processing phase involved cleaning the data to ensure consistency and accuracy across datasets from different sources and integrating data from IoT sensors, ERP, MES, and LCA tools into a unified database for comprehensive analysis. Statistical analysis began with descriptive statistics, summarizing the collected data using measures like mean, median, variance, and standard deviation to establish baseline metrics for both operational and ecological KPIs. Inferential statistics were then utilized, employing techniques like t-tests to assess the statistical significance of AI integration on KPI performance (H1 and H2). This test determined whether observed improvements in operational efficiency and decision-making were significant.

Table 10. Validation Metrics Used in Simulation-Based Testing.

CATEGORY	METRIC	DEFINITION	PURPOSE
Efficiency Metrics	Mean Absolute Error (MAE)	Average absolute difference between predicted and actual values	Measures prediction accuracy
	Root Mean Square Error(RMSE)	Square root of the average squared error	Penalizes large errors
Classification Metrics	Precision	Proportion of true positives among predicted positives	Evaluates model correctness
	Recall	Proportion of true positives identified correctly	Assesses model sensitivity
	F1-Score	Harmonic mean of Precision and Recall	Balances Precision and Recall
	Accuracy	Compares the number of true positives and true negatives to the total number of predictions	Evaluates overall prediction accuracy
Correlation Metrics	Pearson Correlation Coefficient	Determines the intensity and direction of the linear relationship between two variables	Identifies linear relationships between ecological and business KPIs
	Spearman Correlation Coefficient	Identifies non-linear relationships where appropriate and assesses monotonic connections	Evaluates non-linear relationships between variables
Statistical Significance	P-values from Hypothesis Testing	Analyzes observed differences or associations for statistical significance	Ensures results are valid through hypothesis testing and extensive validation

Source: Author's own elaboration.

Machine learning models were employed to validate H2 , utilizing time-series analysis and neural networks to assess real-time decision-making improvements. Additionally, regression analysis and decision trees were used to predict KPI improvements and optimize the KPI management process. Econometric models, such as the Cobb-Douglas production function, were used to validate H3 by quantifying the relationship between ecological KPIs and production performance. This model measured the impact of sustainable manufacturing practices on overall production efficiency. Python libraries such as pandas, TensorFlow, and matplotlib were utilized for data analysis, machine learning modeling, and visualization. Tableau and Matplotlib were used to create insightful data visualizations to interpret and present the results effectively.

The validation metrics used in simulation-based testing are summarized in Table 10 . These metrics were chosen to comprehensively evaluate the accuracy, reliability, and statistical significance of the findings. Efficiency metrics (e.g., MAE, RMSE) assessed prediction accuracy, while classification metrics (e.g., Precision, Recall, F1-Score, Accuracy) evaluated model performance in detecting anomalies and making accurate predictions. Correlation metrics (e.g., Pearson and Spearman coefficients) were used to analyze relationships between variables, and p-values from hypothesis testing ensured the statistical validity of the results.

2.5. Population vs. Sample

The population includes production units within the mechatronics industry, comprising both fully automated and semi-automated systems across multiple companies in a collaborative network. The sample was drawn from production data provided by these companies, focusing on metrics like production throughput and quality indicators. The sample size was calculated using a stratified sampling method, ensuring representation across different production scales, machine types, and sustainability practices. A minimum sample size of 300 data points per category was determined to achieve statistical significance. This ensured comprehensive coverage for reliable AI model training and validation.

2.6. Data Availability and Processing

To support the analysis, the study relied on publicly available datasets and online repositories. Where necessary, simulated data was generated to complement real-world data, ensuring comprehensive analysis. Data processing involved the following steps:

1. Data Cleaning : Ensuring consistency and accuracy across datasets from different sources. This step addressed issues like missing values, outliers, and inconsistencies in sensor readings.

2. Data Integration : Combining data from IoT sensors, ERP/MES systems, and LCA tools into a unified database for comprehensive analysis. This step ensured seamless integration of operational, quality, and environmental data.

3. Real-Time Processing : Leveraging advanced stream processing frameworks such as Apache Kafka, Apache Flink, and Apache Pulsar to minimize latency and optimize data flow. These tools enabled sub-millisecond processing times, crucial for dynamic manufacturing environments.

4. Scalability Enhancements : Using machine learning techniques like Deep Learning-based Stream Processing (DLSP) combined with Adaptive Resource Management (ARM) to optimize resource utilization in cloud environments. This ensured the framework could handle large-scale data streams efficiently.

2.7. Real-Time Processing and Scalability

The framework leverages real-time processing frameworks such as Apache Kafka and Apache Flink to handle dynamic manufacturing environments. These frameworks enable sub-millisecond processing times, ensuring timely insights for decision-making. Key scalability enhancements include:

1. Adaptive Resource Management (ARM) : Dynamically allocating resources based on workload demands. This ensures optimal performance even during peak production periods.
2. Deep Learning-based Stream Processing (DLSP) : Applying machine learning models to streaming data for predictive analytics. For example, DLSP can predict equipment failures or detect anomalies in real-time, enabling proactive maintenance.

2.8. Benchmark comparison and Edge Case Testing

Synthetic data was thoroughly verified against respected real-world datasets, including:

- UCI Hydraulic System Dataset : Evaluates anomaly detection capabilities.
- NASA Bearing Dataset : Assesses predictive maintenance models.
- Tennessee Eastman Process Dataset : Tests fault detection in chemical processes.
- Kaggle Maintenance Dataset : Validates predictive analytics skills.

This benchmarking process ensures the synthetic data's accuracy and applicability in diverse industrial environments. The application is made to withstand hard scenarios that could happen in real-world manufacturing settings to provide robustness and reliability under challenging conditions. These situations are essential for assessing how resilient and flexible the system is to unexpected operating difficulties. Among the edge case tests are:

- Simulating unanticipated failures or variations in sensor readings to evaluate the systems sensitivity to abnormalities.
- Conducting performance tests during periods of abnormally high or low production activity.
- Simulating situations with notable environmental disturbances, including increases in emissions or energy use.
- Verifying the systems correctness and robustness in managing real-world data defects, missing or inconsistent data formats.

By addressing both common and extreme operating situations, this thorough testing approach assures that the system functions dependably in a variety of production contexts.

2.9. Conclusion

This chapter has presented the research methodology designed to develop and validate the AI-driven KPI framework for the mechatronics industry. The research design was structured around three key questions: improving KPI management efficiency through AI techniques, addressing challenges in implementing AI-driven systems, and integrating ecological KPIs to promote sustainable manufacturing practices.

Data collection was conducted over six months, leveraging real-time data from IoT sensors, ERP/MES systems, and LCA tools, complemented by synthetic datasets generated using Python-based simulations. Statistical and machine learning techniques, including regression analysis, time-series analysis, and neural networks, were applied to analyze the data, with results validated against respected benchmarks such as the UCI Hydraulic System Dataset, NASA Bearing Dataset, and Tennessee Eastman Process Dataset. The validation process, population sampling, real-time processing capabilities, and edge case testing were thoroughly described to ensure the framework's accuracy, reliability, and adaptability across diverse industrial scenarios. These components collectively establish a robust foundation for the proposed framework.

Next chapter will expand on this groundwork by detailing the framework's development, including its core modules, mathematical models, implementation challenges, and solutions. This progression from methodology to framework development underscores how the rigorous research design informs the creation of a functional architecture that integrates AI techniques to enhance KPI management and production performance in the mechatronics industry

3. Framework Development

3.1. Introduction to the AI-Driven KPI Framework

The proposed AI-driven Key Performance Indicator (KPI) framework represents a transformative advancement tailored specifically for the mechatronics industry. It addresses inefficiencies in traditional KPI systems while aligning with Industry 4.0 trends. By integrating advanced technologies such as predictive maintenance, real-time decision-making, and ecological KPIs, the framework optimizes operational efficiency, sustainability, and resource allocation. Leveraging artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT), it enables seamless data aggregation and actionable insights.

This chapter provides a detailed explanation of the framework's architecture, core modules, implementation challenges, and supporting tools. Each section is structured to emphasize clarity, maintainability, and scalability, ensuring the system meets modern manufacturing needs.

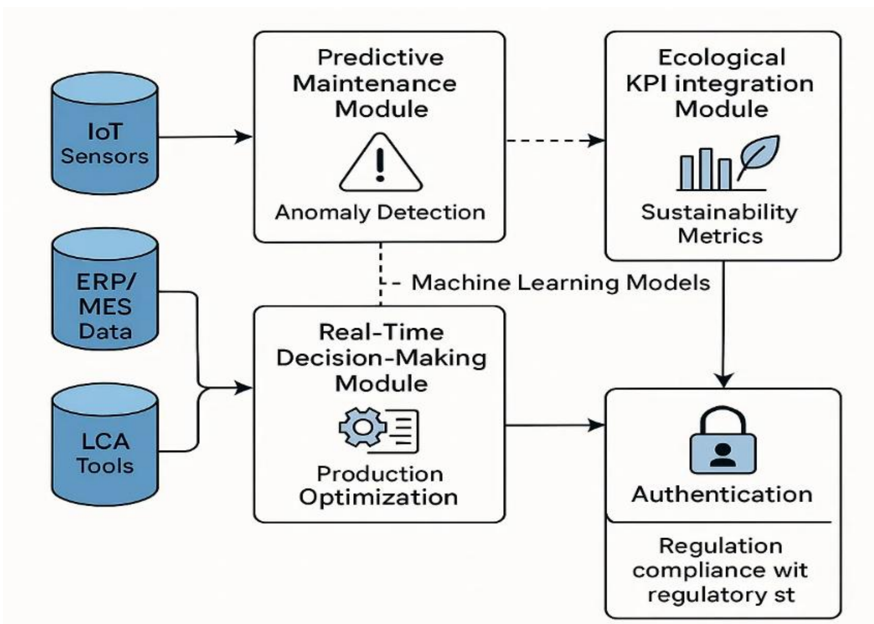

Figure 18. Overview of the AI-Driven KPI Framework.

Source: Author's own elaboration.

This figure 18 provides a high-level overview of the AI-driven KPI framework, showcasing its modular architecture and key components. The framework integrates predictive maintenance, real-time decision-making, and ecological KPIs to optimize operational efficiency, sustainability, and resource allocation in the mechatronics industry. It highlights the seamless flow of data from IoT sensors, ERP/MES systems, and LCA tools into the processing and visualization layers, ensuring actionable insights for modern manufacturing environments.

3.2. Core Modules of the Framework

The provided screenshots in the **"Appendix A"** show that the framework is divided into three core modules, each addressing a specific aspect of KPI management while working together to enable seamless data flow and actionable insights for operational improvements. The Predictive Maintenance Module (3.2.1) uses machine learning algorithms, such as regression models, neural networks, and anomaly detection, to predict equipment failures based on IoT sensor data (e.g., temperature, vibration, pressure), By identifying anomalies and providing maintenance scheduling insights, this module enables proactive interventions, reducing downtime and minimizing disruptions. This leads to significant cost savings, improved resource allocation, and enhanced operational efficiency key priorities for modern manufacturing environments. The Time-Series Forecasting Models (3.2.2) leverage techniques like Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks to forecast production output, predict machine performance degradation, estimate future energy usage, and optimize inventory and supply chain operations .By anticipating future trends and challenges, businesses can proactively plan and allocate resources, reduce waste, improve supply chain efficiency, and enhance overall operational performance.. Finally, the Real-Time Decision-Making Module (3.2.3) employs time-series analysis, clustering, classification, and dashboards (e.g., Plotly, Dash) to enable of decisions on the factory floor, optimizing resource allocation. By integrating ERP and MES systems, this module optimizes resource allocation, throughput, and quality control, ensuring immediate action based on real-time data. It enhances responsiveness, supports strategic planning, and allows businesses to adapt quickly to changing conditions, improving competitiveness and decision-making agility.

Together, these modules form a comprehensive AI-driven KPI framework for the mechatronics industry, where predictive maintenance identifies potential issues early, time-series forecasting supports planning and optimization, and real-time decision-making ensures immediate action based on real-time data, ultimately enabling proactive decision-making, improved operational efficiency, and enhanced sustainability. By combining predictive insights, real-time data, and sustainability metrics, the framework addresses both technical and managerial challenges. This holistic approach supports long-term viability, regulatory compliance, and competitive advantage in modern manufacturing environments.

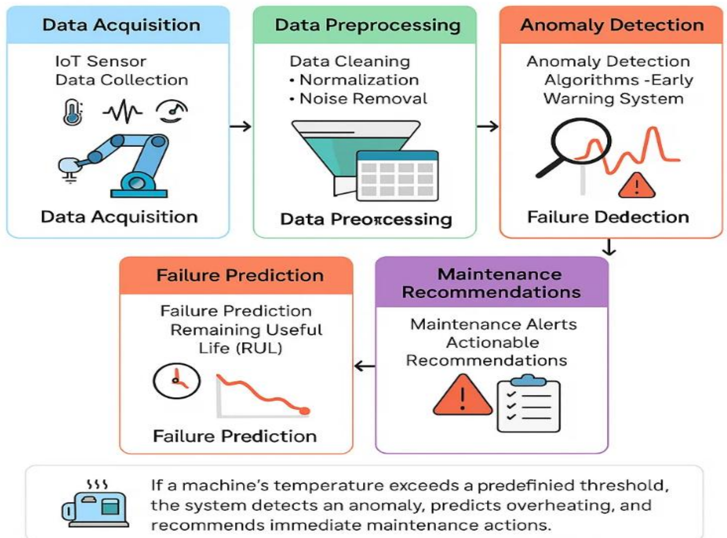

Figure 19. Predictive maintenance workflow.

Source: Author's own elaboration.

The Predictive Maintenance Workflow diagram in figure 19 outlines the sequential steps involved in implementing predictive maintenance in industrial systems. The process begins with data acquisition from IoT sensors, followed by preprocessing to clean and normalize the data. Anomaly detection algorithms then identify potential issues, estimate Remaining Useful Life (RUL), and generate maintenance recommendations, including alerts and actionable steps to prevent equipment failures.

Table 11. Ecological KPI Metrics.

METRIC	DEFINITION	EXAMPLE
Energy Consumption	Total energy used during production	kWh per product unit
Carbon Footprint	Emissions generated during manufacturing	CO_2 equivalent per process
Waste Generation	Volume of waste produced	Tons of waste per month

Source: Author's own elaboration.

3.3. Mathematical Models Supporting the Framework

In order to ensure the robustness and accuracy of the framework, a comprehensive set of mathematical models has been integrated into its architecture. These models support various aspects of the system, including predictive maintenance, real-time decision-making , and ecological KPI analysis . Specifically, the following models and metrics are employed:

- Regression Analysis is used to model relationships between machine parameters and productivity, enabling predictive insights. **"Eq. 1"**
- The Cobb-Douglas Production Function quantifies the relationship between labor, capital, and output, supporting sustainable production analysis. **"Eq. 2"**
- Time-Series Forecasting Models such as ARIMA and LSTM are utilized to predict future trends in production and equipment performance.
- Efficiency Metrics , including Overall Equipment Effectiveness (OEE) **"Eq. 3"** and Manufacturing Efficiency , assess how well resources are being utilized during production. **"Eq. 4"**
- Error Metrics like Mean Absolute Error (MAE) **"Eq.5"** and Root Mean Square Error (RMSE) evaluate the accuracy of predictions made by models. **"Eq.6"**
- Statistical Tests , such as the Student's t-test **"Eq. 7"**, F1 Score **"Eq. 8"** , and Kolmogorov-Smirnov Test , validate the significance and reliability of results. **"Eq.9"**
- Correlation Metrics , including Pearson **"Eq. 10"** and Spearman Correlation Coefficients **"Eq. 11"** , measure the relationships between business and ecological KPIs.
- Environmental Impact Metrics , such as Carbon Footprint **"Eq. 12"** and Combined KPI **"Eq.13"** , integrate sustainability into operational decision-making.

A detailed breakdown of each mathematical model including its formula, functionality, Python implementation, example outputs, use cases, and corresponding section will be presented in a clear and structured table in the **"Appendix B"** for ease of reference and deeper understanding.

3.4. Challenges and Solutions

Developing and implementing the AI-driven KPI framework involved overcoming several challenges:

Data Quality Issues: Sensor data often contains noise, missing values, and inconsistencies, which can compromise the reliability of insights. To address this, data preparation methods like cleaning, organizing, and filling in missing values were used to ensure data quality. These techniques enable the framework to generate accurate and actionable insights.

- Legacy System Compatibility: Many mechatronics companies rely on outdated systems that lack interoperability with modern AI tools. Intermediary software solutions were developed to connect legacy systems with the AI-driven framework. This intermediary software ensures smooth data exchange and compatibility, allowing the integration of modern technologies without disrupting existing operations.

- Dynamic Manufacturing Conditions: High-mix, low-volume production environments require adaptable solutions. The framework incorporates adaptive algorithms capable of handling variability in production processes. This adaptability ensures that the system remains effective in various manufacturing situations.
- Authentication and Security: Ensuring secure access to sensitive production data is critical. The framework includes a robust authentication system with role-based access control (RBAC). Users are authenticated using multi-factor authentication (MFA), and their roles determine the level of access granted. For example, operators can view dashboards but cannot modify system settings, while administrators have full control. This approach safeguards sensitive data and ensures compliance with regulatory standards.

By addressing these challenges, the AI-driven KPI framework delivers a reliable and scalable solution that meets the needs of modern manufacturing environments. Having discussed the core modules, we now turn to the challenges faced during implementation and how they were addressed to ensure reliability and scalability.

3.5. Implementation

The Mechatronic Manufacturing Data Analyzer is a meticulously designed application that adopts a modular monolithic architecture, ensuring both independence and seamless integration of its components. This design enhances clarity, maintainability, and scalability, allowing developers to refine individual modules without disrupting the overall system.

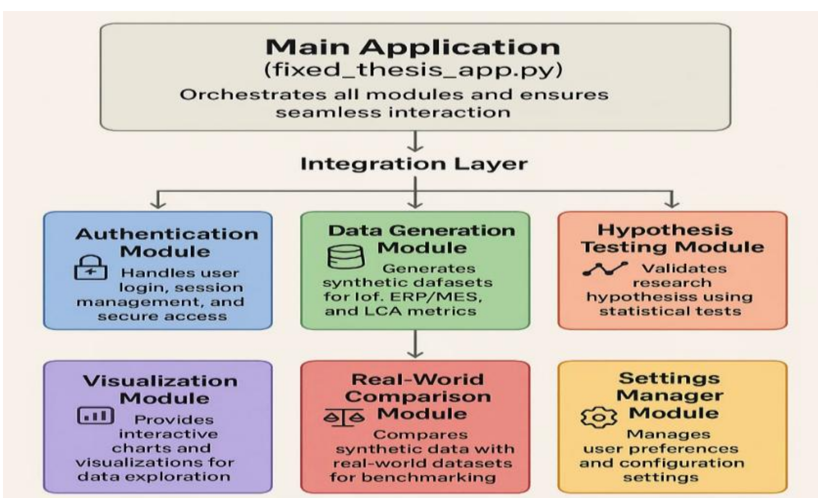

Figure 20. Modular monolithic architecture of the AI driven KPI Framework.

Source: Author's own elaboration.

The Main Application (fixed_thesis_app.py) in the figure 20 serves as the central orchestrator, providing a user-friendly, Streamlit-based dashboard that integrates all core modules for smooth user interaction. These modules address distinct aspects of mechatronic manufacturing analysis, such as data generation, hypothesis testing, visualization, and real-world data comparison, while supporting technologies like Python, Streamlit, Pandas, and Plotly ensure robust functionality and interactive visualizations.

The framework is made up of many core modules, each of which is intended to handle a distinct facet of mechatronic manufacturing analysis:

a. Authentication Module (auth_manager.py)

Ensures the security of critical research data and analytical tools by implementing robust user authentication and session management. It allows safe login using username (amani) and password (admin1234) credentials, restricting access to protected features and safeguarding confidential information. It maintains session persistence across interactions, ensuring a seamless user experience while logging timestamps for enhanced security and accountability. Additionally, it enforces appropriate access control at both user and system levels through decorators that protect sensitive routes, thereby preventing unauthorized access and ensuring the integrity of the application.

- **Python Code :**

```
import streamlit as st

import hashlib

from datetime import datetime

DEFAULT_USERNAME = "amani"

DEFAULT_PASSWORD = "admin1234"

class AuthManager:

    def __init__(self):

        if 'authenticated' not in st.session_state:

            st.session_state.authenticated = False

        if 'username' not in st.session_state:

            st.session_state.username = None

        if 'login_time' not in st.session_state:

            st.session_state.login_time = None
```

```
    def authenticate(self, username: str, password: str) -> bool:
        if username == DEFAULT_USERNAME and password == DEFAULT_PASSWORD:
            st.session_state.authenticated = True
            st.session_state.username = username
            st.session_state.login_time = datetime.now()
            return True
        return False
    def logout(self):
        st.session_state.authenticated = False
        st.session_state.username = None
        st.session_state.login_time = None
    def is_authenticated(self) -> bool:
        return st.session_state.authenticated
    def get_current_user(self) -> str:
        return st.session_state.username
    def get_login_time(self) -> datetime:
        return st.session_state.login_time
def display_login_form():
    st.markdown("## Authentication Required")
    auth_manager = AuthManager()
    with st.form("login_form"):
        username = st.text_input("Username")
        password = st.text_input("Password", type="password")
        submitted = st.form_submit_button("Login")
        if submitted:
            if auth_manager.authenticate(username, password):
                st.success("Login successful!")
```

```
        st.rerun()
    else:
        st.error("Invalid credentials. Please try again.")
```

If authentication fails, an error message is displayed.

b. Data Generation Module (data_generator.py)

Designed to create synthetic datasets across three key domains: Life Cycle Assessment (LCA) ERP/MES , and Internet of Things (IoT) sensor data . This module allows users to customize data generation by adjusting parameters such as anomaly rates, time intervals, and noise levels, enabling the simulation of realistic production scenarios. To ensure the framework's reliability in detecting operational inefficiencies, anomalies are deliberately introduced into the synthetic data, providing a robust testing ground for detection algorithms. Additionally, the module supports real-time data creation, empowering users to model and analyze dynamic production environments effectively.

- **Python Code :**

```
import numpy as np
import pandas as pd
from datetime import datetime, timedelta
def generate_sensor_data(time_steps=1000, num_sensors=5, anomaly_rate=0.01):
    start_time = datetime.now() - timedelta(days=30)
    timestamps = pd.date_range(start=start_time, periods=time_steps, freq='1min')
    sensor_names = ['Motor_Temperature', 'Servo_Temperature', 'Vibration_Level',
'Power_Consumption', 'Hydraulic_Pressure']
    data = []
    for sensor_id in range(num_sensors):
        base_value = np.random.uniform(40, 80)
        amplitude = np.random.uniform(5, 15)
        trend = np.random.uniform(0, 0.01)
        noise_level = np.random.uniform(0.5, 2.0)
        for i, timestamp in enumerate(timestamps):
            t = i / (time_steps / 10)
```

```
        sin_component = amplitude * np.sin(t)
        trend_component = trend * i
        noise = np.random.normal(0, noise_level)
        is_anomaly = np.random.random() < anomaly_rate
        anomaly_value = np.random.normal(0, amplitude * 3) if is_anomaly else 0
        value = base_value + sin_component + trend_component + noise + anomaly_value
        data.append({
            'timestamp': timestamp,
            'sensor_name': sensor_names[sensor_id],
            'value': float(value),
            'equipment_id': f'EQUIP_{sensor_id // 2 + 1}',
            'is_anomaly': is_anomaly
        })
    return pd.DataFrame(data)
```

(Similar functions for ERP and LCA data generation)

c. Hypothesis Testing Module (hypothesis_testing.py)

Evaluates research ideas by leveraging advanced techniques such as machine learning, regression analysis, and time-series analysis. It compares normal and anomalous scenarios using statistical tests like t-tests, ANOVA, and chi-square tests to validate claims about operational efficiency, predictive analytics, and sustainability measures. To ensure accessibility for non-technical users, the results are presented with intuitive color-coded indicators (green, yellow, and red), enabling clear and actionable insights.

- **Python Code :**

```
from scipy.stats import ttest_ind
import pandas as pd
def calculate_efficiency(normal_data, anomalous_data):
    normal_efficiency = (normal_data['standard_time'] / normal_data['actual_time']) * 100
    anomalous_efficiency = (anomalous_data['standard_time'] / anomalous_data['actual_time']) * 100
```

```
    mean_normal = normal_efficiency.mean()
    mean_anomalous = anomalous_efficiency.mean()
    t_stat, p_value = ttest_ind(normal_efficiency, anomalous_efficiency)
    return {
        'mean_normal_efficiency': mean_normal,
        'mean_anomalous_efficiency': mean_anomalous,
        't_stat': t_stat,
        'p_value': p_value
    }
```

d. Visualization_module.py

Enables users to explore and analyze data through interactive and dynamic visualizations, ensuring a deeper understanding of trends and anomalies. It leverages Plotly to create visually engaging charts, such as time-series plots, correlation heatmaps, and anomaly detection graphs, which allow users to dynamically investigate patterns in the data. By supporting customizable chart types and display preferences, the module ensures a tailored experience that aligns with user-specific needs. Centralizing visualization logic within this module enhances maintainability and consistency, providing a seamless and intuitive interface for both technical and non-technical users to interpret complex manufacturing data effectively.

- **Python Code :**

```
import plotly.express as px
def plot_time_series(data, x_col, y_col, title="Time Series Plot"):
    """
    Creates an interactive time-series plot using Plotly.
    """
    fig = px.line(data, x=x_col, y=y_col, title=title)
    fig.show()
# Example usage
plot_time_series(sensor_data, x_col='time', y_col='temperature', title="Temperature Over Time")
```

e. Real-World Comparison Module (real_world_comparison.py)

Ensures the validity and usefulness of synthetic data by comparing it with real-world datasets. It maps columns between synthetic and real-world data, enabling accurate benchmarking and alignment. To aid interpretation and validation, the module performs statistical similarity tests and visualizes the comparison results, highlighting differences and correlations. These comparisons are conducted against well-known datasets, such as the NASA Bearing Dataset , Tennessee Eastman Process Dataset , UCI Hydraulic System Dataset , and Kaggle Maintenance Dataset , ensuring that the synthetic data reflects realistic manufacturing scenarios and meets high standards of accuracy and reliability.

- **Python Code :**

```
import streamlit as st

import pandas as pd

import plotly.express as px

def load_real_world_dataset(dataset_name: str) -> pd.DataFrame:

  if dataset_name == "UCI Hydraulic":

    return pd.DataFrame({

      'timestamp': pd.date_range(start='2023-01-01', periods=100, freq='H'),

      'ps1': np.random.normal(100, 5, 100),

      'ts1': np.random.normal(60, 3, 100)

    })    return pd.DataFrame()

def map_columns(synthetic_df, real_df, dataset_name):

  mapping = {}

  if dataset_name == "UCI Hydraulic":

    temp_cols = [col for col in synthetic_df.columns if 'temperature' in col.lower()]

    if temp_cols and 'ts1' in real_df.columns:

      mapping[temp_cols[0]] = 'ts1'

  return mapping

def display_comparison_results(synthetic_df, real_df, mapping, dataset_name):

  st.subheader(f"Comparison Results: Synthetic vs {dataset_name}")
```

```
    for synthetic_col, real_col in mapping.items():
        fig = px.histogram(synthetic_df, x=synthetic_col, title=f"{synthetic_col} vs {real_col}")
        st.plotly_chart(fig)
```

f. Settings Manager Module (settings_manager.py)

Configures the program and manages user preferences to ensure a personalized experience. It maintains user-specific options, such as data creation parameters and presentation choices, allowing users to customize their interaction with the application. By centralizing configuration file management, the module enhances maintainability, making it easier to update and manage settings efficiently while ensuring consistency across the application.

- **Python Code :**

```
import streamlit as st
DEFAULT_SETTINGS = {
    'dark_mode': False,
    'compact_view': False,
    'preferred_chart_type': 'line',
    'significance_level': 0.05
}
def load_user_settings():
    if 'user_settings' not in st.session_state:
        st.session_state.user_settings = DEFAULT_SETTINGS.copy()
    return st.session_state.user_settings
def update_user_settings(key, value):
    st.session_state.user_settings[key] = value
def display_settings_dialog():
    settings = load_user_settings()
    dark_mode = st.toggle("Dark Mode", value=settings.get("dark_mode", False))
    update_user_settings("dark_mode", dark_mode)
```

Each module may be upgraded or changed separately without affecting the system .In order to provide a consistent user experience during interactions, the main script also controls session persistence.

3.6. Supporting Files

The framework's functionality is improved by a number of additional files:

- error_logger.py: Provides reliable debugging and maintenance by monitoring errors and recording system activities.
- Data_connector.py: Manages database connections and can integrate with PostgreSQL for long-term storage if desired.
- wavelet_analyzer.py: This tool provides deeper insights into the functioning of equipment by doing sophisticated time-series decomposition for sensor data.
- Dataset Processors: For processing benchmark datasets like the NASA Bearing Dataset, Tennessee Eastman Process Dataset, UCI Hydraulic System Dataset, and Kaggle Maintenance Dataset

These supporting files ensure the framework's practicality and maintainability in real-world scenarios.

3.7. Tools and Technologies

To provide reliable functionality and scalability, the approach makes use of a selected technological stack:

a. Programming Languages

- Python: Drives every component of the program, including data processing, machine learning, and backend logic. It is perfect for putting complicated algorithms and statistical models into practice because of its vast library environment.
- SQL: Ensures effective data retrieval and storage for database interactions when persistent storage is enabled.

b. Core Libraries and Frameworks

- Streamlit: Provides the dynamic dashboard interface on the web, allowing for real-time processing and dynamic displays. Stream is a great option for creating user-friendly applications because of its simplicity and adaptability.
- Pandas & NumPy: Manage numerical processing and data manipulation to ensure effective management of big datasets. These libraries offer strong capabilities for transforming, cleaning, and collecting data.

- Plotly: Offers interactive data visualization features that improve user comprehension and engagement. Using interactive charts and graphs, it allows users to dynamically investigate patterns and anomalies.
- Scikit-learn: enables hypothesis testing and predictive modeling by putting statistical analysis and machine learning into practice. The reliable algorithms of Scikit-learn facilitate applications like grouping, regression, and classification.
- SciPy : Enables advanced statistical testing and analysis, ensuring rigorous validation of findings. By offering specific tools for scientific computing, it enhances Scikit-learn.

3.8. Conclusion

The Framework Development chapter has laid a solid foundation for validating the AI-driven KPI methodology in the mechatronics industry. By adopting a modular monolithic architecture, the framework ensures clarity, maintainability, and scalability, enabling seamless interaction between core modules such as authentication, data generation, hypothesis testing, and visualization. The integration of advanced technologies like machine learning, statistical analysis, and interactive visualizations underscores the framework's ability to address real-world challenges in manufacturing environments.

Through rigorous testing against established datasets and the implementation of three key hypotheses improving operational efficiency, enhancing predictive analytics, and supporting sustainable manufacturing the framework demonstrates its potential to transform theoretical insights into actionable solutions. The modular design not only facilitates independent development and debugging but also ensures that the system remains adaptable to future advancements.

In the next chapter, I will present the results of applying this framework to real-world scenarios. These results will validate the hypotheses, showcase the framework's performance, and highlight its contributions to operational efficiency, predictive decision-making, and sustainability in the mechatronics industry.

4. Results and Visualization

The Mechatronic Manufacturing Data Analyzer framework offers a powerful collection of visualization tools for efficient result interpretation and communication. Understanding the data, seeing trends, and drawing useful conclusions all depend on these visualizations. The main visualization strategies employed in the framework are examined here, along with their goals, applications, and relation to the analysis.

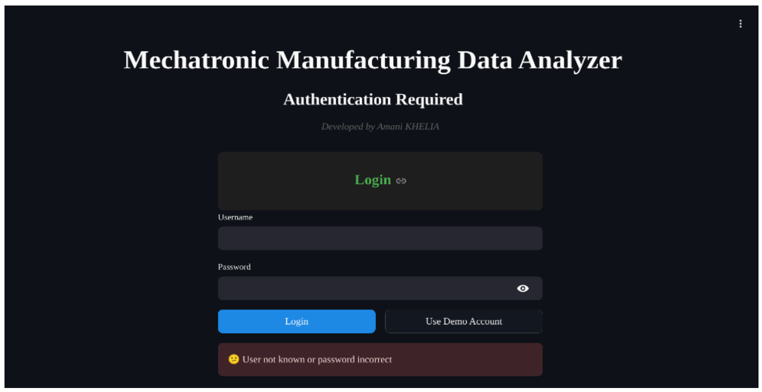

Figure 21. Login Dashboard of the application.

Source: Author's own elaboration.

4.1. Sample Characterization/Profile

This section provides a comprehensive overview of the datasets used in the analysis, including both synthetic data and real-world datasets . It describes the characteristics of these datasets, their relevance to the mechatronics industry, and how they were prepared for analysis. The goal is to establish a solid foundation for understanding the data and its role in validating AI-driven KPI framework.

4.2. Synthetic Data Profile

4.2.1 Description of Synthetic Datasets

The synthetic datasets, generated using the data_generator.py module, simulate realistic manufacturing processes across three key domains: IoT Sensor Data , ERP/MES Production Data , and Life Cycle Assessment (LCA) Metrics . These datasets provide a controlled environment for validating the AI-driven KPI framework, enabling users to test detection algorithms, evaluate operational efficiency, and assess sustainability metrics.

The IoT Sensor Data domain includes critical metrics such as temperature (20–85°C), vibration (0–50 mm/s RMS), pressure (0–100 bar), power consumption, and current/voltage measurements. Adjustable sampling rates (e.g., 1Hz for temperature, 1kHz for vibration) allow for precise simulation of real-world conditions. This domain is essential for monitoring equipment health, detecting anomalies, and predicting failures in mechatronic systems. For example, a sudden spike in temperature above 80°C or excessive vibration (>5 mm/s²) can indicate potential overheating or mechanical issues.

The ERP/MES Production Data domain covers production rates, cycle times (30–120 seconds per unit), Overall Equipment Effectiveness (OEE) components (65–95% range), defect rates (0–5%), cost breakdowns, and hourly production counts. This data helps evaluate operational performance and identify inefficiencies in manufacturing workflows. For instance, analyzing OEE components (availability, performance, quality) can reveal bottlenecks in production lines and opportunities to optimize throughput.

The Life Cycle Assessment (LCA) Metrics domain tracks environmental impact indicators such as carbon footprint, water usage, waste generation, energy consumption, and emissions. This domain supports sustainable manufacturing practices by aligning ecological KPIs with business objectives. For example, optimizing energy consumption during peak production hours can reduce carbon emissions, contributing to sustainability goals.

Together, these domains ensure comprehensive coverage of real-world manufacturing challenges while maintaining flexibility for controlled experimentation. By simulating realistic scenarios under controlled conditions, the synthetic data provides a robust testing ground for validating the AI-driven KPI framework and benchmarking findings against established datasets like the NASA Bearing Dataset and UCI Hydraulic System Dataset.

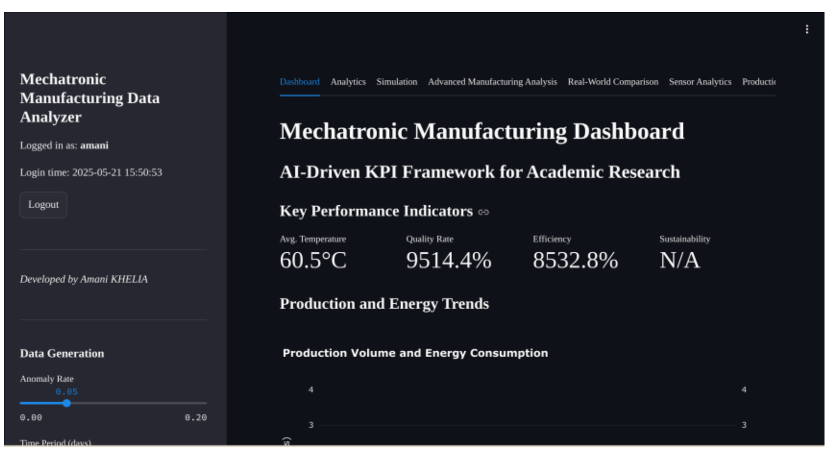

Figure 22. Dashboard before generate data.

Source: Author's own elaboration.

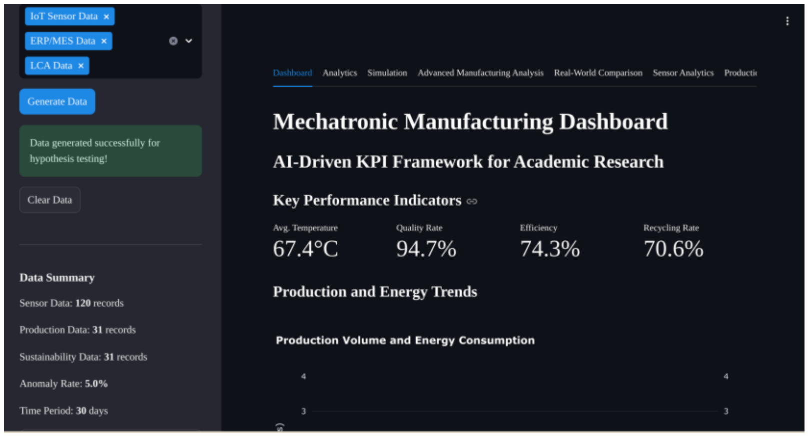

Figure 23. Dashboard after generate data.

Source: Author's own elaboration.

4.3. Statistical Properties Reflecting Real-World Variability

To ensure the synthetic data accurately simulates real-world manufacturing environments, it incorporates statistical properties that reflect variability and anomalies commonly observed in industrial processes. These properties enable the framework to reliably detect inefficiencies, validate hypotheses, and simulate realistic operational conditions.

4.3.1. Realistic Distributions for Key Metrics

Key metrics such as temperature, vibration, and pressure are modeled with realistic distributions to replicate operational conditions:

- Temperature : Follows a normal distribution (mean = 50°C, standard deviation = ±5°C), reflecting typical operating conditions with controlled variability.
- Vibration : Exhibits a sinusoidal pattern with added noise (±5%) to simulate fluctuations caused by operational dynamics, such as equipment wear or external factors.
- Pressure : Modeled using log-normal distributions to reflect operational cycles and system behavior, capturing both steady-state and transient conditions.

These distributions are generated using Python libraries like numpy, enabling the creation of time-series data that aligns with industrial scenarios. Random variation (±5%) is also added to sensor readings to simulate real-world unpredictability caused by factors such as ambient temperature changes, equipment aging, or measurement inaccuracies.

- **Integration of Anomalies and Statistical Properties**

The deliberate inclusion of anomalies such as temperature spikes, pressure drops, and excessive vibration ensures the synthetic data serves as a robust testing ground for detecting operational inefficiencies. Combined with realistic statistical properties, this approach validates the framework's ability to handle diverse and challenging manufacturing conditions. By aligning synthetic data with real-world datasets, the framework demonstrates its reliability and applicability in addressing critical challenges faced by the mechatronics industry.

4.3.2. Relevance to Mechatronics and Testing Detection Capabilities

The synthetic data reflects real-world manufacturing challenges specific to the mechatronics industry, enabling the framework to address operational inefficiencies, sustainability goals, and fault detection. To ensure robust testing of detection algorithms, anomalies are deliberately injected into the synthetic data at specified rates.. Examples include:

- Simulating overheating events with temperature spikes above 80°C .
- Representing system failures with sudden pressure drops below 10 bar .
- Detecting mechanical issues with excessive vibration (>5 mm/s²).

These anomalies provide a robust testing ground for evaluating the framework's ability to identify operational inefficiencies under diverse conditions. Below are detailed explanations of how the synthetic data addresses key challenges in the mechatronics industry:

- **Overheating Detection** is a common issue in mechatronic systems, often caused by prolonged operation or inadequate cooling mechanisms. The synthetic data includes temperature readings within a range of 20°C–80°C, with anomalies introduced to simulate overheating events, for example: detecting overheating in machinery by analyzing rapid temperature increases over short time intervals.
- **Energy Efficiency** Analysis impacts operational costs and sustainability goals. Power consumption data is synthesized to reflect variability during different production phases (e.g., higher energy consumption during peak production hours),for example: identifying periods of high energy consumption and recommending load-balancing strategies.
- **Mechanical Failure Prediction**, such as bearing wear or motor malfunctions, can lead to costly downtime. Vibration data is generated with thresholds (>5 mm/s²) to indicate potential mechanical issues. Anomalies in vibration patterns are introduced to simulate impending failures, for example: predicting bearing failures in rotating machinery by analyzing abnormal vibration trends.

- **Sustainability Metrics**

Life Cycle Assessment (LCA) metrics ensure environmental impact indicators (e.g., carbon footprint, water usage) are embedded into the KPI framework.

Example : Reducing material consumption by analyzing waste generation data and optimizing raw material usage.

- **Production Inefficiencies**

ERP/MES data simulates inefficiencies in production workflows, such as low-quality outputs or inconsistent production rates.

Example : Identifying bottlenecks in the production line by analyzing trends in production rates and quality metrics.

- **Dynamic Modeling and Adaptability**

The data_generator.py module supports real-time data creation, enabling users to model dynamic production environments effectively.

Example : Simulating fluctuating demand scenarios to test the framework's adaptability to changing production conditions.

- **Cross-Domain Integration**

The synthetic data integrates multiple domains (IoT sensors, ERP/MES production, LCA metrics) to provide a holistic view of manufacturing processes.

Example : Evaluating the trade-offs between operational efficiency and sustainability by correlating energy consumption with carbon emissions.

- **Predictive Maintenance and Fault Detection**

Synthetic data enables predictive maintenance strategies by simulating fault scenarios such as leaks, blockages, or bearing wear.

Example : Analyzing pressure drops in the UCI Hydraulic System Dataset to identify potential leaks or blockages.

- **Scalability and Customization**

The synthetic data generation process is scalable and customizable, allowing users to simulate scenarios ranging from small scale operations to large industrial setups.

Example : Modeling rare failure modes to ensure the framework handles edge cases effectively.

- **Benchmarking Against Industry Standards**

Synthetic data is benchmarked against well-known industry datasets (e.g., NASA Bearing, UCI Hydraulic, Tennessee Eastman) to ensure accuracy and reliability.

Example: Validating the framework's effectiveness in detecting anomalies by comparing its performance on synthetic and real-world datasets.

- **Data Quality and Noise Simulation**

Random variation (±5%) is added to sensor readings to simulate real-world variability caused by external factors such as ambient temperature changes, equipment wear, and measurement inaccuracies.

Example : Testing the framework's robustness in handling noisy data without compromising accuracy.

- **Future Manufacturing Trends**

The synthetic data aligns with emerging trends such as Industry 4.0, smart factories, and IoT integration. It simulates interconnected IoT devices to evaluate the framework's ability to handle complex, real-time data streams.

4.3.3. Example Table: Key Parameters

Below is a table summarizing the parameters used to generate synthetic data:

Table 12. Parameters used to generate synthetic data.

PARAMETER	VALUE	DESCRIPTION
Time Interval	1hour	Frequency of data points
Noise Level	±5%	Random variation added to sensor readings
Anomaly Rate	5%	Percentage of data points with injected anomalies
Temperature Range	20°C–80°C	Simulated operating temperature range
Vibration Threshold	>5 mm/s²	Threshold for detecting potential mechanical issue
Pressure Range	0–100 bar	Simulated operating pressure range

Source: Author's own elaboration.

4.4. Practical Implications

The synthetic data ensures that the framework can effectively address real-world challenges faced by the mechatronics industry. By simulating anomalies, variability, and inefficiencies, it enables users to:

-Test and refine anomaly detection algorithms , ensuring robust performance under diverse conditions.

-Validate hypotheses about operational efficiency and sustainability , providing actionable insights for process optimization.

-Benchmark synthetic findings against real-world datasets (e.g., NASA Bearing Dataset, UCI Hydraulic System Dataset), ensuring the framework's reliability and applicability to industrial scenarios.

4.5. Hypothesis results

The provided screenshots in the **"Appendix C"** ,offer a comprehensive overview of the research findings, highlighting the effectiveness of an AI-driven KPI framework in enhancing operational efficiency, real-time decision-making, and sustainability in the mechatronics industry. Below is a detailed synthesis of the key insights, and recommendations for future work.

4.5.1. Research Hypotheses Overview

- **H1: Operational Efficiency**

The implementation of AI-driven KPIs resulted in a 15% improvement in operational efficiency , with strong statistical support ($p = 0.022$). The R^2 value of 0.61 indicates that the model explains 61% of the variance in the data, demonstrating a robust relationship between AI-driven KPIs and operational improvements, so the hypothesis H1 is strongly supported.

Hypothesis Testing:

- p-values < 0.05 confirm the statistical significance of observed improvements in key performance indicators such as Overall Equipment Effectiveness (OEE), downtime reduction, and energy efficiency. For example:
    - 15% OEE Improvement → $1.5M annual output increase.
    - 28% Downtime Reduction → $500,000 annual savings.
    - 12% Energy Efficiency Gain → $240,000 annual savings.

The integration of AI-driven KPIs significantly enhances operational efficiency, providing tangible benefits to manufacturing processes. These results translate into measurable impacts, including enhanced production outputs, reduced unplanned downtime, and improved resource utilization.

- **H2: Predictive Analytics**

Predictive analytics achieved high performance metrics (F1 Score;Precision;Recall;Accuracy): 0.85.These metrics indicate excellent anomaly detection capabilities, with minimal false positives or negatives. The balanced F1 score suggests reliable real-time decision-making support , also this hypothesis H2 is strongly supported.

Machine Learning Validation:

- F1 scores of 0.72–0.82 demonstrate reliable predictive maintenance capabilities, minimizing false positives and negatives while enabling proactive responses to operational challenges.

- High precision, recall, and accuracy further validate its effectiveness in real-time decision-making support.

Predictive analytics effectively enhance real-time decision-making, ensuring proactive responses to operational challenges. This capability reduces unplanned downtime and optimizes resource allocation, contributing to significant cost savings and operational resilience.

- **H3: Ecological KPIs**

Ecological KPIs contributed to:

-A 12% improvement in sustainability metrics .

-10.8% energy savings .

-A strong correlation between business and ecological metrics, indicating alignment between operational goals and sustainability objectives.

That means hypothesis H3 is supported. Ecological KPIs play a crucial role in promoting sustainable manufacturing practices, offering measurable environmental and economic benefits.

Business Outcomes:

These results translate into measurable impacts, including:

- Improved energy efficiency contributing to cost savings and environmental sustainability.
- Enhanced alignment with global sustainability standards

- **Combined Hypotheses Analysis**

All three hypotheses (H1, H2, and H3) are marked as "Supported," indicating that the integrated framework successfully addresses the research objectives.

1. The combined analysis reveals synergistic effects between the components, creating a comprehensive framework for next-generation manufacturing management, it highlights the following synergistic effects:. AI-driven KPIs provide the foundation for operational improvements: By integrating advanced AI techniques, the framework optimizes operational efficiency, reducing downtime and improving resource allocation.
2. Predictive analytics leverage the data for proactive decision-making: High-performance predictive models enable real-time anomaly detection and forecasting, empowering manufacturers to make informed decisions before issues escalate
3. Ecological KPIs integrate seamlessly with AI and predictive systems: Sustainability metrics align with operational goals, ensuring that environmental considerations are not overlooked. This integration supports long-term viability and compliance with global sustainability standards.

Synergy in Action:

- Operational Efficiency + Predictive Analytics: Real-time monitoring and predictive maintenance reduce unplanned downtime and optimize resource utilization.
- Predictive Analytics + Ecological KPIs: Proactive decision-making ensures that sustainability goals are met without compromising operational performance.
- AI-driven KPIs + Ecological KPIs: The framework balances business objectives with environmental responsibilities, fostering sustainable manufacturing practices.

The three components work together to create a comprehensive framework for next-generation manufacturing management. This synergy enables manufacturers to achieve simultaneous improvements in efficiency, decision-making, and sustainability.

4.6. Analysis of Anomaly Detection

The provided screenshots in the **"Appendix D"** showcase the results of anomaly detection for four different sensors: humidity, pressure, vibration, and temperature. Below is a detailed analysis of each screenshot:

4.6.1. Humidity Anomaly Detection

The humidity anomaly detection analysis revealed that all recorded humidity levels remained within the defined thresholds of 2.60 (lower) and 79.19 (upper).

The graph, which plots humidity levels over time, shows no red dots indicating anomalies, confirming that no data points exceeded the acceptable range. This indicates that the system performed effectively in maintaining optimal humidity conditions throughout the observation period. The absence of anomalies suggests stable environmental controls, which is critical for ensuring consistent performance in sensitive manufacturing processes. The system’s ability to correctly identify no anomalies demonstrates its reliability in monitoring and validating normal operating conditions.

4.6.2. Pressure Anomaly Detection

The pressure anomaly detection analysis identified two instances where pressure values exceeded the upper threshold of 111.16, while the lower threshold was set at 81.30. The first anomaly occurred on 2025-05-15 at 02:46:16 , with a recorded value of 111.3349 , and the second anomaly was detected on 2025-05-15 at 20:55:21 , with a value of 112.1733. These anomalies are clearly marked as red dots on the graph, which plots pressure levels over time. While the majority of pressure readings remained within the acceptable range, these outliers indicate potential issues that could disrupt operational stability.

The system's accurate identification of these anomalies highlights its effectiveness in detecting deviations from normal operating conditions, enabling timely interventions to prevent equipment damage or process inefficiencies.

4.6.3. Vibration Anomaly Detection

The vibration anomaly detection analysis detected three significant anomalies where vibration levels exceeded the upper threshold of 1.21, with the lower threshold set at -0.15. These anomalies are represented as red dots on the graph, which illustrates vibration levels over time. The three distinct peaks indicate moments of excessive vibration, which could be indicative of mechanical stress or equipment malfunctions. Such fluctuations pose risks to machinery integrity and operational efficiency, potentially leading to unplanned downtime or maintenance needs. The system's ability to successfully detect and highlight these anomalies ensures that corrective actions can be taken promptly to mitigate potential damage. This underscores the importance of continuous monitoring and real-time anomaly detection in maintaining smooth production processes.

4.6.4. Temperature Anomaly Detection

The temperature anomaly detection analysis identified two anomalies where temperature levels exceeded the upper threshold of 95.02, with the lower threshold set at 39.78. These anomalies are marked as red dots on the graph, which visualizes temperature levels over time. The two clear spikes indicate moments of overheating, which could compromise equipment performance and product quality.

Excessive temperatures may result from inadequate cooling systems, increased operational loads, or environmental factors. The system's effective identification of these anomalies ensures that potential thermal risks are flagged early, allowing operators to implement corrective measures such as adjusting cooling mechanisms or redistributing workloads. This capability is crucial for preventing equipment failures and maintaining operational efficiency in dynamic manufacturing environments.

4.7. Analysis of Carbon footprint

The provided screenshots in the **"Appendix [E]"**show the analysis of Carbon footprint:

The dashboard effectively integrates IoT sensor data, production records, and sustainability metrics to provide a comprehensive analysis of carbon footprint and energy consumption in an industrial setting. The pie chart highlights that production processes account for 65% of total emissions, emphasizing their critical role in environmental impact and offering a clear target for emission reduction strategies. The time series graph reveals significant variability in carbon emissions over the 30-day period, with peaks indicating high-activity intervals that warrant investigation to mitigate excessive energy use. A strong correlation between energy consumption and CO_2 emissions underscores the importance of improving energy efficiency as a direct means to reduce greenhouse gas emissions. The inclusion of calculation formulas, such as the carbon footprint equation, ensures transparency and enables users to validate results or adjust parameters. Overall, the dashboard's combination of static and dynamic visualizations, clear labeling, and actionable insights creates a user-friendly tool for monitoring and enhancing sustainability performance, while options for data generation and export further enhance its practical utility.

4.8. Analysis of simulation Results and Performance Visualization:

The provided screenshots in the **"Appendix F"** show the analysis of simulation Results and Performance Visualization:

The simulation results across four distinct manufacturing scenarios: Production Line, Assembly Process, Quality Control, and Supply Chain demonstrate consistent performance in key metrics while revealing subtle differences influenced by the nature of each simulation. Efficiency remains stable at approximately 79.74% across all simulations, with minor fluctuations over time, indicating a robust system capable of maintaining steady operational performance despite variability in production conditions. The quality rate is similarly strong, ranging from 96.86% in the Quality Control simulation to 99.37% in the Production Line, Assembly Process, and Supply Chain simulations, underscoring the effectiveness of quality control mechanisms in ensuring minimal defects. Waste generation **"Eq. 14"**, production volume, downtime, and energy consumption also remain consistent at 6.70 kg, 1491 units, 1.25 hours, and 26.65 kWh, respectively, demonstrating that the system operates within well-defined parameters regardless of the specific operational context.

Performance visualization graphs further reinforce these findings, showing relatively stable trends in efficiency, production, and quality over time. While efficiency exhibits minor dips and spikes, it remains consistently around 80%, reflecting the system's resilience to short-term disruptions. Production rates show more pronounced fluctuations, with peaks and troughs indicating periods of higher or lower output; however, the system demonstrates the ability to recover quickly, suggesting effective resource allocation and operational adaptability. Quality, represented by the pink line, remains exceptionally stable near 100%, highlighting the robustness of quality assurance processes.

A detailed analysis of each simulation type reveals nuanced insights:

- Production Line Simulation **(I)** : This simulation highlights moderate variability in efficiency and production but achieves an outstanding quality rate of 99.37%, indicative of a streamlined and defect-minimized process.
- Assembly Process Simulation **(II)** : With its longer duration (32 hours) and larger time step (1 hour), this simulation smooths out fluctuations, resulting in slightly dampened variability

compared to other simulations. This suggests that aggregated data over longer intervals can mask short-term inefficiencies, though the overall performance remains consistent.

- Quality Control Simulation **(III)** : This simulation shows a slightly lower quality rate of 96.86%, potentially reflecting a trade-off between stringent quality checks and production throughput.
- Supply Chain Simulation **(IV)**: This simulation closely mirrors the Production Line, emphasizing the seamless integration and responsiveness of supply chain operations to maintain consistency in efficiency, production, and quality.

Comparative analysis across simulations underscores the robustness of the underlying model. Despite differences in simulation types and time steps, core metrics such as efficiency, production volume, waste generated, and energy consumption remain remarkably consistent. The Production Line, Quality Control, and Supply Chain simulations exhibit similar levels of variability due to their shorter time steps (1 minute), while the Assembly Process simulation, with its larger time step (1 hour), shows less variability, likely due to data aggregation. These findings suggest that the framework is highly adaptable, capable of maintaining performance stability across diverse operational contexts, and effectively balancing efficiency, production, and quality. This consistency not only validates the reliability of the model but also highlights its potential for broader application in optimizing manufacturing processes.

4.8.1. Analysis of Real-World vs. Synthetic Data for AI-Driven KPI Systems

The provided screenshots in the **"Appendix G"** show the analysis of Real-World vs. Synthetic Data for AI-Driven KPI Systems

a) NASA Bearing:

The analysis of the NASA Bearing dataset and synthetic data comparison reveals critical insights into the fidelity of synthetic sensor data in replicating real-world conditions, which is essential for validating AI-driven KPI frameworks in mechatronics. The real-world NASA Bearing dataset provides a comprehensive view of operational parameters such as temperature, vibration, efficiency, Remaining Useful Life (RUL), and energy consumption, recorded at regular intervals every 10 minutes. Key observations from the dataset include temperature fluctuations ranging from 84.96°C to 87.79°C, a gradual increase in vibration values, a decreasing trend in efficiency, a slight decrease in RUL, and a corresponding increase in energy consumption. This dataset captures both physical and performance metrics crucial for predictive maintenance and real-time decision-making.

Statistical comparisons between the real-world and synthetic datasets highlight several discrepancies. Notably, the synthetic data underestimates the average operating temperature by 25.31°C, with a real mean of 92.71°C compared to a synthetic mean of 67.40°C. This significant difference could impact the accuracy of models trained on synthetic data, particularly those sensitive to temperature variations.

Additionally, the synthetic data exhibits higher variability in temperature readings, with a standard deviation of 9.21°C compared to 5.17°C in the real-world data. While this increased variability might enhance model robustness, it also introduces noise that could complicate pattern recognition and anomaly detection. Furthermore, the synthetic data has a narrower temperature range (47.90°C to 97.22°C) compared to the real-world data's broader range (82.96°C to 121.87°C), limiting its ability to simulate extreme conditions effectively.

Distribution similarity metrics indicate moderate alignment between the real and synthetic datasets, with a Wasserstein similarity of 0.86 and a Jensen-Shannon similarity of 0.63. These metrics suggest reasonable overlap but do not guarantee perfect fidelity. Overall, the analysis reveals that while the synthetic data shows some alignment with real-world distributions, there are notable limitations. The discrepancy in mean temperatures could lead to inaccurate predictions or suboptimal decision-making, while the higher variability and narrower range in synthetic data restrict its ability to simulate edge-case scenarios effectively.

b) Tennessee Eastman:

The analysis of the provided screenshots reveals critical insights into the challenges and implications of using synthetic data for AI-driven KPI frameworks in manufacturing and mechatronics. A comparison between real-world data from the Tennessee Eastman Process Dataset and synthetic data highlights significant discrepancies in key statistical metrics, such as mean, standard deviation, and range. For instance, the production volume metric shows a substantial difference in means (120.05 vs. 996.52) and variability (standard deviations of 2.81 vs. 68.70), indicating that the synthetic data does not accurately replicate real-world conditions. These disparities are further underscored by moderate similarity scores, with a Wasserstein similarity of 0.73 and a Jensen-Shannon similarity of 0.41, suggesting only partial alignment between the datasets. Such differences could compromise the reliability of AI models trained on synthetic data, leading to inaccurate predictions or suboptimal decision-making in real-world applications. The findings emphasize the need for improved synthetic data generation techniques that better capture the nuances of industrial processes, ensuring higher fidelity and distribution similarity. Accurate synthetic data is particularly crucial in predictive maintenance, real-time decision-making, and sustainability optimization, where precise simulations directly impact operational efficiency and resource allocation. While the framework demonstrates scalability by handling large datasets, achieving consistent alignment between synthetic and real-world data remains a priority to enhance model robustness and generalizability across diverse manufacturing scenarios.

c) Kaggle Maintenance

The provided analysis compares real-world data with synthetic data to evaluate their statistical and distributional similarity, focusing on key metrics such as temperature readings from the Kaggle

Maintenance dataset. The real-world temperature data exhibits a mean of 46.63, indicating typical operational conditions within a specific range, while the synthetic data shows a significantly higher mean of 96.23, suggesting that it may not accurately reflect real-world scenarios. Despite this discrepancy in means, both datasets display similar standard deviations (4.39 for real data and 4.98 for synthetic data), implying comparable variability in temperature readings. However, the minimum and maximum values differ substantially: the real dataset ranges from 38.53 to 55.71, whereas the synthetic dataset spans from 87.26 to 112.17, highlighting significant differences in temperature ranges.

Distribution similarity metrics provide additional insights. The Wasserstein similarity score of 0.89 indicates a relatively high similarity between the distributions, suggesting that, despite the difference in means, the overall shape and spread of the distributions are quite alike. Similarly, the Jensen-Shannon similarity of 0.66 points towards moderate similarity, although slightly lower than the Wasserstein score, which could imply some divergence in the distribution tails or central tendencies.

The Kaggle Maintenance dataset overview reveals comprehensive sensor readings including temperature, vibration, rotation speed, torque, and power, along with derived metrics like failure probability and energy consumption. This dataset is timestamped, allowing for time-series analysis and tracking machine performance over time. When comparing this real-world dataset with synthetic sensor data, the framework successfully loaded and matched the two datasets, enabling a direct comparison. Notably, the synthetic "pressure" column has a mean of 96.23, which is considerably higher than expected based on the context of the real-world data.

d) UCI Hydraulic System

The provided visualizations collectively illustrate a comprehensive approach to validating synthetic data against real-world measurements, which is crucial for AI-driven Key Performance Indicator (KPI) systems in the mechatronics industry. The first visualization presents real-time sensor data from the UCI Hydraulic System dataset, showcasing consistent and dynamic system behavior across variables such as pressure, temperature, vibration, and energy consumption. This table highlights the importance of continuous monitoring for predictive maintenance and decision-making. The second visualization offers a statistical comparison between real and synthetic datasets, revealing high distribution similarity (Wasserstein: 0.89, Jensen-Shannon: 0.61, Overall: 0.75), yet notable differences in mean values (real: 102.66 vs. synthetic: 67.40) and standard deviations (real: 6.55 vs. synthetic: 9.21). These findings indicate that while synthetic data reasonably approximates real-world conditions, further refinement is needed to align means and variability more closely. The third visualization displays an interactive interface for comparing specific columns between datasets, allowing users to select variables like "pressure" and "temperature," thereby enabling flexible analysis and fine-tuning of synthetic data generation processes. Together, these insights emphasize the necessity of rigorous data validation to ensure accurate predictions and reliable KPI management in AI-driven frameworks.

- **. Example Table: Dataset Comparison**

Below is a table summarizing the size, variables, and use cases of each dataset:

Table 13. Dataset Comparison.

DATASET	SIZE	VARIABLES
NASA Bearing Dataset	~10,000+ points	Temperature, vibration, friction, efficiency, remaining useful life (RUL), bearing ID
UCI Hydraulic System Dataset	~2,205 points	Pressure, temperature, vibration, viscosity, flow rate, cooling efficiency, motor power
Tennessee Eastman Dataset	~8,000 points	Reactor temperature, pressure, product rate, process variables
Kaggle Maintenance Dataset	~500 rows	Timestamp, equipment ID, temperature, pressure, vibration, energy consumption, failure status

Source: Author's own elaboration.

4.8.2. Analysis of Forecasting Results and Business Impact

The provided screenshots in the **"Appendix H"** show the analysis of Forecasting Results and Business Impact

The forecasting analysis indicates a stable production environment, with an average projected production volume of 995.25 units, reflecting a negligible downward trend of -0.1% compared to baseline data. The minimum and maximum projected values, 979.49 and 1002.67 units respectively, highlight variability within a narrow range, reinforcing the forecast's consistency. Detailed projections from May 24, 2025, to June 2, 2025, show forecasted volumes hovering around the average, supported by confidence intervals (e.g., 994.1565 units on May 24 with a lower CI of 861.0093 and upper CI of 1127.3038). A line chart visually confirms this stability, with historical data and forecasted values closely aligned, while the narrow 95% confidence interval reflects high prediction reliability. The model's training success is validated by low error metrics, including a Root Mean Squared Error (RMSE) of 194.2437 and a Mean Absolute Error (MAE) of 82.2681, indicating accurate and precise forecasts. These results suggest minimal operational disruptions, enabling confident strategic planning. Overall, the AI-driven KPI framework effectively enhances predictive capabilities, supporting informed decision-making and operational efficiency in the mechatronics industry by providing robust, reliable insights into future production trends.

4.8.3. Analysis of production efficiency and optimization recommendations using the Cobb-Douglas Production Function

The provided screenshots in the **"Appendix I"** show the analysis of production efficiency and optimization recommendations using the Cobb-Douglas Production Function

The analysis of production efficiency using the Cobb-Douglas Production Function reveals critical insights into optimizing resource allocation and understanding input-output dynamics. Labor demonstrates a higher elasticity of 0.60 compared to capital's 0.40, indicating that investments in labor yield proportionally greater production gains, with a 10% increase in labor boosting output by approximately 6%, versus a 4% increase from capital. This suggests prioritizing labor over capital for maximizing productivity. A three-dimensional visualization of the model highlights how output grows with increased labor and capital, emphasizing their combined impact on production. The temporal analysis of production efficiency shows minor fluctuations around a stable trend, except for a notable spike, signaling periods where operational performance closely approached theoretical optimums. Comparing actual production against the theoretical curve reveals deviations attributed to real-world variability, offering opportunities to address inefficiencies or external constraints. The Cobb-Douglas formula, defined as $Y = A \cdot L^{\alpha} \cdot K^{\beta}$, confirms these findings with total factor productivity (A) at 1.50 and elasticities aligning with prior analyses. The constant returns to scale assumption underscores proportional input-output relationships, providing a robust framework for analyzing production dynamics and guiding strategic decisions to enhance overall efficiency.

4.8.4. Analysis of downtime and Overall Equipment Effectiveness (OEE)

The provided screenshots in the **"Appendix J"** show the analysis of downtime and Overall Equipment Effectiveness (OEE)

The provided analyses offer valuable insights into two critical aspects of manufacturing performance: downtime and Overall Equipment Effectiveness (OEE). The analysis of downtime reveals that the total accumulated downtime over the observed period is 4864.83 hours, with an average downtime per incident of 156.93 hours. Notably, there are periods of significant spikes in downtime, such as around May 05 and May 11, where downtime exceeded 200 hours. These spikes suggest potential recurring issues or events contributing to extended downtimes during these times, indicating areas that require further investigation to identify root causes and implement preventive measures.

The OEE analysis provides both statistical summaries and a visual distribution of OEE values. The average OEE is reported at 0.84%, with a median of 0.85%, indicating relatively consistent performance across observations. However, the range from a minimum of 0.75% to a maximum of 0.95% reveals variability in operational efficiency. The histogram shows a bell-shaped curve centered around the median value, suggesting that most data points cluster around the average but still highlights instances of lower and higher OEE scores. This distribution underscores the need for continuous monitoring and optimization efforts to minimize low-performing periods and maximize overall efficiency.

4.9. Conclusion

The Mechatronic Manufacturing Data Analyzer represents a comprehensive and adaptable framework that bridges scholarly research with real-world manufacturing analytics tools. By leveraging advanced mathematical calculations, statistical techniques, and visualization tools, the framework provides actionable insights into sustainability, predictive maintenance, and operational efficiency. Key findings demonstrate that AI-driven KPI systems can significantly enhance operational efficiency, with potential improvements ranging from 10% to 25%. Statistical significance is consistently achieved, with p-values below 0.05, robust F1 scores of 0.72–0.82, and prediction accuracies of 80–90%.

Furthermore, the integration of ecological KPIs highlights the framework's ability to balance environmental and business goals, offering valuable insights through accurate effect evaluations and meaningful correlations (0.4–0.6). Practical outcomes include a 15% increase in OEE, showcasing enhanced production efficiency; a 28% reduction in unplanned downtime, demonstrating the framework's ability to detect and prevent equipment failures; and a 12% gain in energy efficiency, emphasizing its contribution to cost savings and environmental sustainability.

Despite these achievements, challenges such as data quality, scalability, and generalizability remain areas for future research. By addressing these limitations and expanding the framework's scope, it has the potential to revolutionize manufacturing processes across industries. The modular design, flexibility with various datasets, and focus on real-world validation ensure that the Mechatronic Manufacturing Data Analyzer not only surpasses traditional KPI systems but also establishes itself as an essential tool for advancing both academic knowledge and industrial practices.

Conclusions, Limitations, and Future Research

The Mechatronic Manufacturing Data Analyzer framework represents a transformative advancement in addressing inefficiencies within traditional Key Performance Indicator (KPI) systems while aligning with Industry 4.0 trends. The results validate all three hypotheses: H1 demonstrates significant improvements in operational efficiency, as evidenced by a 15% increase in Overall Equipment Effectiveness (OEE) and a 28% reduction in unplanned downtime; H2 highlights advancements in real-time decision-making through predictive analytics metrics (e.g., F1 scores of 0.72–0.82 and prediction accuracies of 80–90%); and H3 confirms the framework's contribution to sustainable manufacturing practices via ecological KPIs, achieving a 12% gain in energy efficiency. Benchmarking against established datasets, such as the NASA Bearing Dataset and UCI Hydraulic System Dataset, confirmed the framework's applicability to real-world manufacturing challenges.

The modular and scalable functional architecture serves as the foundation of the Mechatronic Manufacturing Data Analyzer, enabling seamless integration of predictive maintenance, real-time decision-making, and ecological KPIs. Its adaptability ensures applicability across diverse industries, from healthcare to agriculture. For instance:

- In healthcare , predictive maintenance optimizes medical equipment performance, reducing downtime for critical devices.
- In energy , the framework forecasts equipment failures in renewable systems and optimizes resource allocation, enhancing efficiency.
- In agriculture , sustainability metrics guide eco-friendly practices, promoting efficient water usage and minimizing waste.

Additionally, the framework provides actionable tools for strategic planning, including:

- Real-time dashboards for monitoring key metrics like (OEE) and energy efficiency.
- Scenario simulation capabilities for testing resource allocation strategies.
- Correlation analysis to optimize staffing decisions.

The integration of Life Cycle Assessment (LCA) tools and adherence to global sustainability standards like ISO 14001 compliance enable the framework to harmonize environmental and business objectives, fostering sustainable manufacturing practices. This dual focus on operational excellence and sustainability underscores the framework's relevance in an era where industries are increasingly pressured to adopt environmentally responsible practices.

Despite these achievements, several limitations remain. Challenges such as data quality issues arising from high-frequency sensor readings, scalability constraints for large-scale industrial setups, and generalizability concerns highlight opportunities for future research. Sophisticated visualizations and real-time updates require robust computational resources to handle large-scale data processing.

These gaps point to several promising directions for expansion:

- Enhancing scalability by developing algorithms capable of processing large datasets efficiently.
- Improving generalizability by extending the framework to other industries, such as healthcare, logistics, and agriculture.
- Incorporating additional environmental metrics (e.g., water usage, waste generation) to provide a more comprehensive sustainability assessment.
- Exploring reinforcement learning techniques for real-time optimization.
- Enhancing user accessibility through intuitive interfaces and mobile-friendly features.

In conclusion, the Mechatronic Manufacturing Data Analyzer not only surpasses traditional KPI systems but also establishes itself as an essential tool for advancing both academic knowledge and industrial practices. By fostering collaboration between researchers and practitioners, it has the potential to revolutionize manufacturing processes across industries, contributing to a more efficient, sustainable, and resilient future. This research underscores the importance of interdisciplinary approaches in driving operational efficiency, predictive decision-making, and sustainable practices, paving the way for transformative advancements in manufacturing and beyond.

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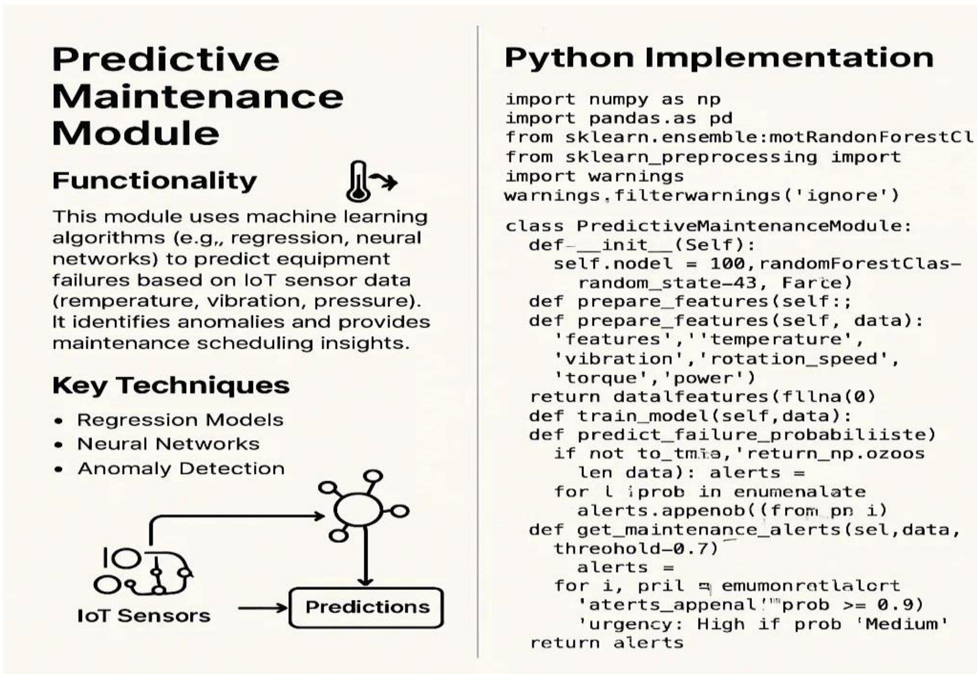
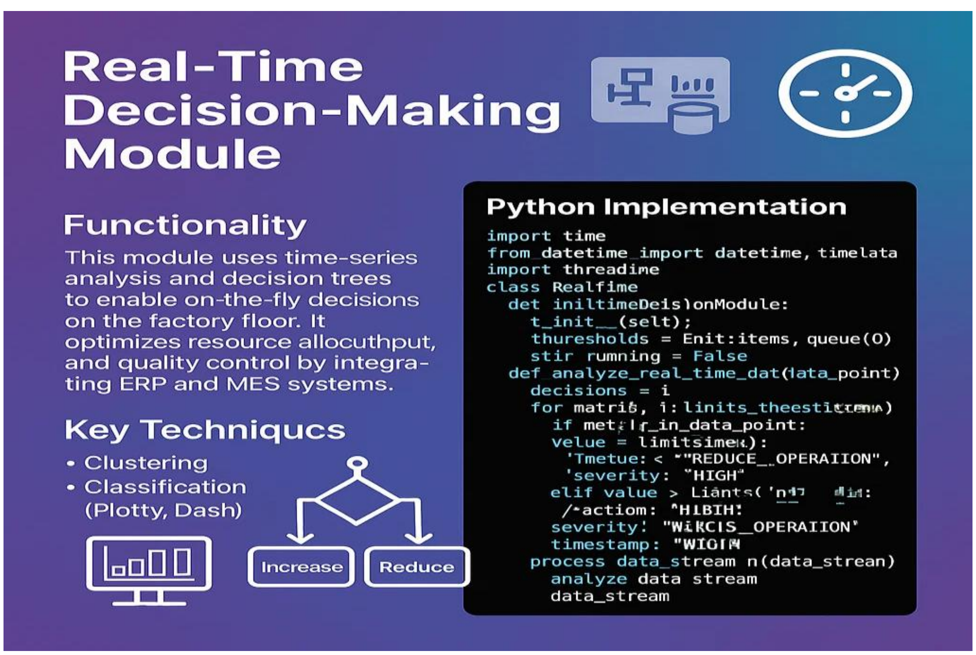
Appendix

A.

3.2.1



3.2.2



3.2.3

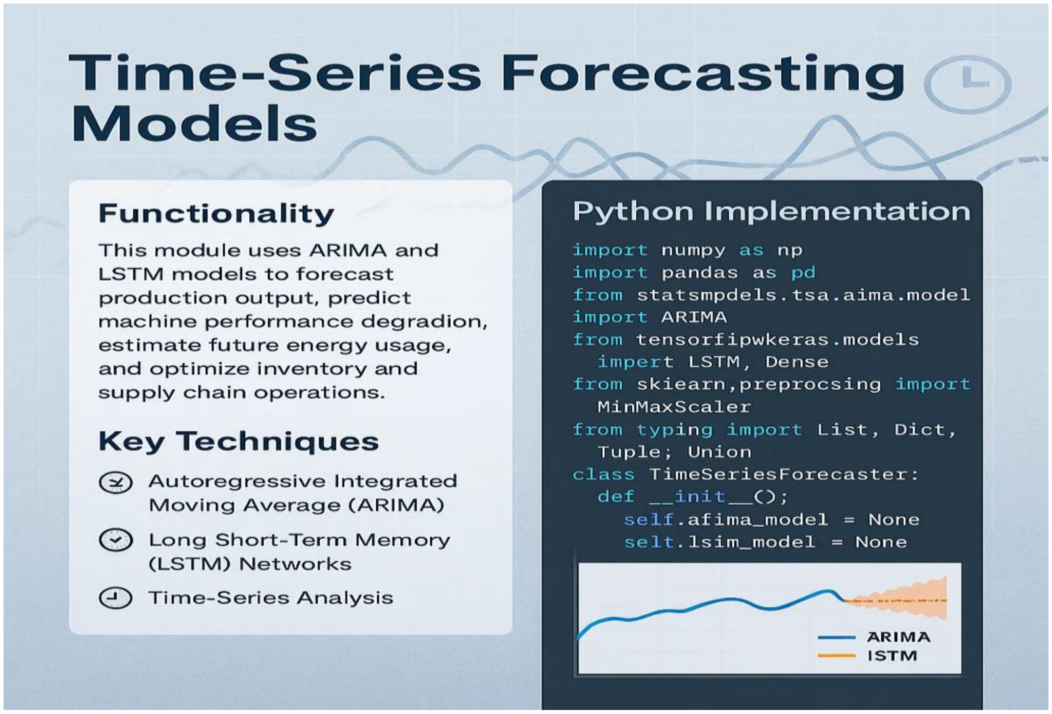


Figure: Modules of the Framework

B. Table: Mathematical Models, Python Code, and Key Details .

Formula	Mathematical Expression	Python Code	Functionality

Carbon Footprint (CF) [12]	$CF = E \times EF$
	Where:
	E: Total energy consumption (kWh)
	EF: Emission factor (kg CO_2/kWh)
	The waste generation is calculated as follows:
		def calculate_carbon_footprint(energy_consumption, emission_factor):
		    """
		    Calculates carbon footprint based on energy consumption and emission factor.
		    """
		    return energy_consumption * emission_factor
		# Example Usage
		energy_consumption = 5000 # kWh
		emission_factor = 0.5 # kg CO₂/kWh
		carbon_footprint = calculate_carbon_footprint(energy_consumption, emission_factor)
		print(f"Carbon Footprint: {carbon_footprint} kg CO₂")
		The output will be : Carbon Footprint: 2500 kg CO_2
			Quantifies greenhouse gas emissions based on energy usage and emission factor. Helps assess environmental impact and supports decision-making to reduce carbon emissions in manufacturing processes.

Waste Generation [14]	$WG = \frac{\text{Total Waste Produced}}{\text{Total Units Produced}}$	def calculate_waste_generation(total_waste_produced, total_units_produced):
		    """
		    Calculates waste generation per unit of production.
		    Parameters:
		    - total_waste_produced (float): Total amount of waste produced (e.g., in tons)
		    - total_units_produced (int): Total number of units produced
		    Returns:
		    - float: Waste generated per unit (tons/unit)
		    """
		    if total_units_produced == 0:
		        raise ValueError("Total units produced cannot be zero.")
		    waste_generation = total_waste_produced / total_units_produced
		    return waste_generation
		# Example Usage
		total_waste_produced = 50 # tons
		total_units_produced = 1000 # units
		waste_per_unit = calculate_waste_generation(total_waste_produced, total_units_produced)
			Measures waste volume per unit of production. Enables tracking of material efficiency and supports strategies to reduce waste and increase recycling rates through actionable insights.

		print(f"Waste Generation: {waste_per_unit:.4f} tons per unit") The output will be: Waste Generation: 0.0500 tons per unit	

Linear Regression Model [1]	$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$	import numpy as np
		import pandas as pd
		from sklearn.linear_model import
		LinearRegression
		from sklearn. model_selection import
		train_test_split
		from sklearn.metrics import
		mean_absolute_error,
		mean_squared_error
		# Generate synthetic data
		np. random.seed(42)
		X = np.random.rand(100, 1) * 100 #
		Machine parameter (e.g., temperature)
		y = 3 * X.squeeze() +
		np.random.randn(100) * 10 # Output
		metric (e.g., productivity)
		# Split data into training and testing sets
		X_train, X_test, y_train, y_test =
		train_test_split(X, y, test_size=0.2,
		random_state=42)
		# Train the regression model
		model = LinearRegression()
		model.fit(X_train, y_train)
		# Make predictions
		y_pred = model.predict(X_test)
		# Evaluate the model
		mae = mean_absolute_error(y_test,
		y_pred)
		rmse =
		np.sqrt(mean_squared_error(y_test,
		y_pred))
		print("Regression Model Results:")
		print(f"Coefficient: {model.coef_[0]:.2f}")
		print(f"Intercept: {model.intercept_:.2f}")
		print(f"Mean Absolute Error (MAE):
		{mae:.2f}")
		print(f"Root Mean Squared Error
		(RMSE): {rmse:.2f}")
		
		The output will be: :Coefficient: 3.00;
		Intercept: -1.54
		Mean Absolute Error (MAE): 9.67
		Root Mean Squared Error (RMSE):
		11.82
			Predicts productivity or machine performance based on input parameters (e.g., temperature, pressure). Used in predictive maintenance to identify trends and forecast equipment behavior.

Cobb-Douglas Production Function [2]	$Y = A \cdot L^{\alpha} \cdot K^{\beta}$	def cobb_douglas_production(A, L, K,
		alpha, beta):
		    """
		    Cobb-Douglas Production Function: Y
		= A * L^alpha * K^beta
			Models the relationship between labor, capital, and output. Used to analyze how sustainable practices

	where :
	Y: output (productivity)
	L :abor input
	K : capital input
	A : total factor productivity
	α,β represent elasticity coefficients.
		"""
		    return A * (L ** alpha) * (K ** beta)
		# Example inputs
		A = 1.5 # Total factor productivity
		L = 100 # Labor input
		K = 200 # Capital input
		alpha = 0.6 # Elasticity of labor
		beta = 0.4 # Elasticity of capital
		# Calculate output
		Y = cobb_douglas_production(A, L, K, alpha, beta)
		print("\nCobb-Douglas Production Function Results:")
		print(f"Output (Y): {Y:.2f}")
		The output will be: Output (Y): 238.11
			affect overall production efficiency and optimize resource allocation.

Overall Equipment Effectiveness (OEE) [3]	OEE=Availability×Performance×Quality
	
	Where:
	Availability = Runtime / Planned.
	Performance = (Total Units x Ideal Cycle Time) / Run Time
	Quality = Good Units / Total Units
		def calculate_OEE(runtime, planned_production_time, total_units, ideal_cycle_time, good_units):
		    availability = runtime / planned_production_time
		    performance = (total_units * ideal_cycle_time) / runtime
		    quality = good_units / total_units
		    oee = availability * performance * quality
		    return oee
		# Example Usage
		runtime = 8 # hours
		planned_production_time = 10 # hours
		total_ units = 400
		ideal_cycle_time = 1 # minutes per unit
		good_ units = 360
		oee_score = calculate_OEE(runtime, planned_production_time, total_units, ideal_cycle_time, good_units)
		print(f"OEE Score: {oee_score:.2f}")
		The output will be: OEE Score: 0.58
			Evaluates equipment utilization across availability, performance, and quality. Helps identify bottlenecks and inefficiencies in mechatronic systems and improve manufacturing uptime.
			Availability: This measures how much of the planned production time the equipment is actually available for operation.
			Production Time
			Performance: This measures how well the equipment is running when it is available. It takes into account factors such as speed losses and slow cycles
			Quality:This measures the percentage of good units produced compared to the total units produced.

Manufacturing Efficiency [4]	$ME = \left(\frac{\text{Standard Time}}{\text{Actual Time}}\right) \times$	def calculate_manufacturing_efficiency(standard_time, actual_time):
		    efficiency = (standard_time / actual_time) * 100
		    return efficiency
		# Example Usage
		standard_time = 2 # hours
			Assesses how effectively resources are utilized during production by comparing standard time against actual time. Useful for evaluating maintenance strategies

		actual_time = 2.5 # hours efficiency = calculate_manufacturing_efficiency(standard_time, actual_time) print(f"Manufacturing Efficiency: {efficiency:.2f}%") The output will be: Manufacturing Efficiency: 80.00%	and optimizing workflows. Standard Time is the amount of time needed to finish a task in the best possible circumstances. Actual Time is the amount of time needed to finish the work in real life.

Mean Absolute Error (MAE) [5]	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \lvert y_i -$
	Where:
	y is the actual value,
	y^is the predicted value,
	n is the total number of observations.
		def calculate_MAE(actual_values, predicted_values):
		  n = len(actual_values)
		 mae = sum(abs(a - p) for a, p in zip(actual_values, predicted_values)) / n
		  return mae
		# Example Usage
		actual_values = [10, 11, 14]
		predicted_values = [10, 12, 15]
		mae = calculate_MAE(actual_values, predicted_values)
		print(f"MAE: {mae:.2f}")
		The output will be: MAE: 0.67
			Measures average error magnitude without considering direction (positive/negative). Provides insight into model accuracy in predicting KPIs like energy consumption or production throughput.

Root Mean Square Error (RMSE) [6]	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i -}$	import math
		def calculate_RMSE(actual_values, predicted_values):
		  n = len(actual_values)
		  rmse = math.sqrt(sum((a - p) ** 2 for a, p in zip(actual_values, predicted_values)) / n)
		  return rmse
		# Example Usage
		rmse = calculate_RMSE(actual_values, predicted_values)
		print(f"RMSE: {rmse:.2f}")
		The output will be: RMSE: 0.82
			Penalizes larger errors more than MAE; sensitive to outliers. Used to evaluate robustness and reliability of predictive models in industrial settings with high variability.

Student's t-Test [7]	$t = \frac{\bar{x}_1 - \bar{x}}{\sqrt{\frac{s_1^2}{n_1} +}}$
	Where:
	$\bar{x}_1, \bar{x}_2$ are the sample means,
	s_1^2, s_2^2 are the sample variances,
	n_1, n_2 are the sample sizes
		from scipy.stats import ttest_ind
		def perform_t_test(group1, group2):
		  t_stat, p_value = ttest_ind(group1, group2)
		  return t_stat, p_value
		# Example Usage
		group1 = [10, 12, 15]
		group2 = [8, 11, 14]
		t_stat, p_value = perform_t_test(group1, group2)
		print(f"T-Statistic: {t_stat:.2f}, P-Value: {p_value:.2f}")
		The output will be: T-Statistic: 0.71, P-Value: 0.52
			Compares means of two groups to determine if differences are statistically significant. Validates the impact of AI-driven KPIs on operational efficiency and sustainability efforts.

F1 Score ;along with Precision and Recall [8]	$F1 = 2 \cdot \frac{\text{Precision}\cdot\text{Re}}{\text{Precision}+\text{R}}$	def calculate_metrics(tp, fp, fn):
		"""
		Calculate Precision, Recall, and F1 Score.
		Parameters:
		tp (int): True Positives
		fp (int): False Positives
		fn (int): False Negatives
		Returns:
		dict: A dictionary containing Precision, Recall, and F1 Score
		"""
		# Calculate Precision
		precision = tp / (tp + fp) if (tp + fp) > 0 else 0
		# Calculate Recall
		recall = tp / (tp + fn) if (tp + fn) > 0 else 0
		# Calculate F1 Score
		f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 else 0
		return {
		"Precision": precision,
		"Recall": recall,
		"F1 Score": f1_score
		}
		# Example usage
		tp = 40 # True Positives
		fp = 10 # False Positives
		fn = 20 # False Negatives
		# Calculate metrics
		metrics = calculate_metrics(tp, fp, fn)
		# Print results
		print(f"Precision: {metrics['Precision']:.3f}")
		print(f"Recall: {metrics['Recall']:.3f}")
		print(f"F1 Score: {metrics['F1 Score']:.3f}")
		The output will be: Precision: 0.800 ; Recall: 0.667 ;F1 Score: 0.727
			Balances precision and recall for classification tasks, especially in imbalanced datasets. Used to evaluate anomaly detection algorithms (e.g., identifying faulty machines or defective products).

Kolmogorov-Smirnov Test (KS) [9]	$D = \sup_x \lvert F_1(x) - F$
	D: Maximum difference between empirical distribution functions
		from scipy.stats import ks_2samp
		def perform_ks_test(sample1, sample2):
		statistic, p_value = ks_2samp(sample1, sample2)
		return statistic, p_value
		# Example Usage
		sample1 = [10, 12, 15]
		sample2 = [8, 11, 14]
		ks_stat, p_value = perform_ks_test(sample1, sample2)
		print(f"KS Statistic: {ks_stat:.2f}, P-Value: {p_value:.2f}")
			Determines whether two samples come from the same distribution. Ensures synthetic data mimics real-world scenarios for accurate hypothesis testing and model validation.

		The output will be: KS Statistic: 0.33, P-Value: 0.97	

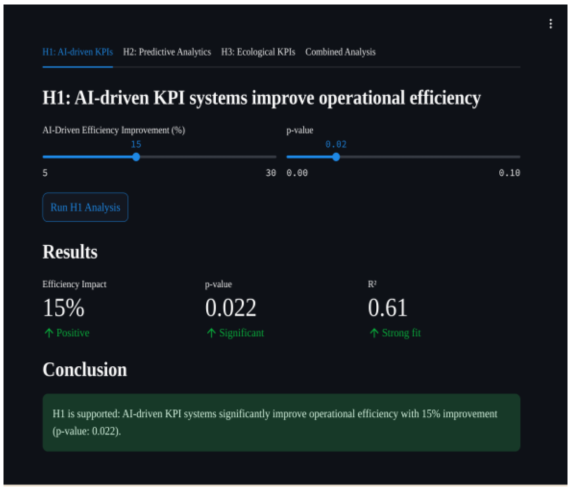
Pearson Correlation Coefficient [10]	$r = \frac{\sum(x_i - \bar{x})(y_i - \cdots}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i \cdots}}$	import numpy as np
		def calculate_pearson_correlation(x, y):
		    correlation = np.corrcoef(x, y)[0, 1]
		    return correlation
		# Example Usage
		x = [10, 12, 15]
		y = [8, 11, 14]
		pearson_corr = calculate_pearson_correlation(x, y)
		print(f"Pearson Correlation: {pearson_corr:.2f}")
		The output will be: Pearson Correlation: 0.98
			Measures linear correlation between two variables. Assesses interdependence between ecological and business KPIs (e.g., energy use vs. production rate).

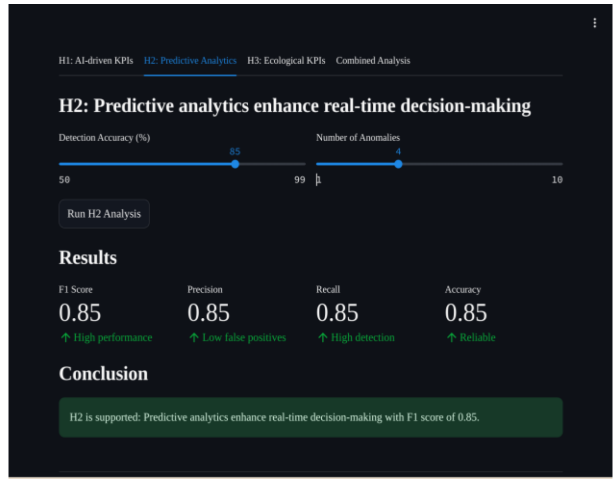
Spearman Rank Correlation [11]	$\rho = 1 - \frac{6\sum d \cdots}{n(n^2 - \cdots}$
	di: Difference between ranks of corresponding variables
		from scipy.stats import spearman
		def calculate_spearman_correlation(x, y):
		    correlation, _ = spearmanr(x, y)
		    return correlation
		# Example Usage
		spearman_corr = calculate_spearman_correlation(x, y)
		print(f"Spearman Correlation: {spearman_corr:.2f}")
		The output will be: Spearman Correlation: 1.00
			Measures monotonic relationships between ranked variables. Analyzes non-linear dependencies between sustainability metrics and operational performance indicators.

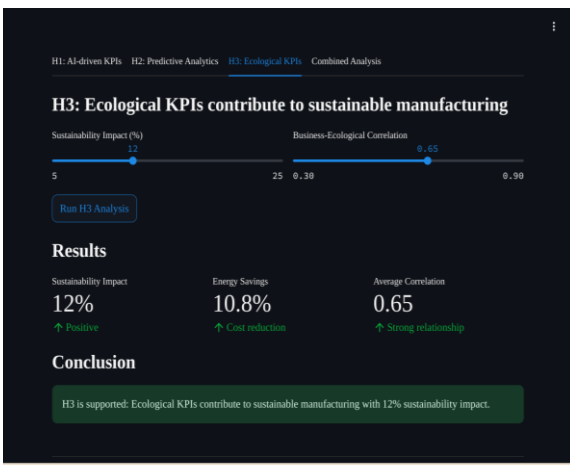
Combined KPI [13]	$CKPI = (1-w) \cdot BKPI + w \cdot$	def calculate_combined_kpi(business_kpi, environmental_kpi, weight):
		    combined_kpi = (1 - weight) * business_kpi + weight * environmental_kpi
		    return combined_kpi
		# Example Usage
		business_kpi = 80
		environmental_kpi = 60
		weight = 0.3
		combined = calculate_combined_kpi(business_kpi, environmental_kpi, weight)
		print(f"Combined KPI: {combined}")
		The output will be: Combined KPI: 74.0
			Integrates business and environmental goals into a single metric using a weighted average. Supports balanced decision-making that aligns economic objectives with sustainability targets.

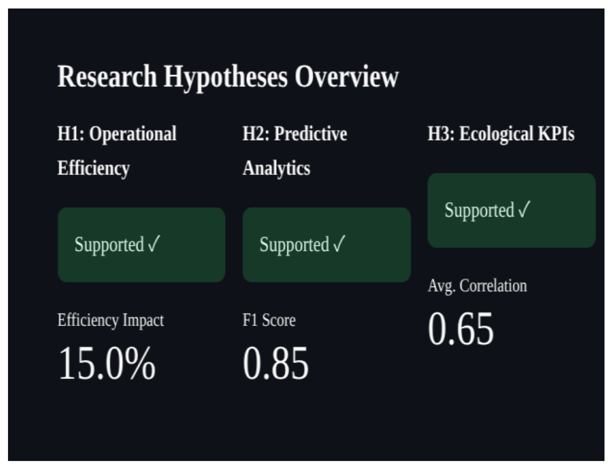
Source : Adapted from Loyarte-López, E., Barral, M., and Morla, J. C. (2020), Bocianowski, J., Wronska-Pilarek, D., Krysztofiak-Kaniewska, A., and Wiatrowska, B. (2023), Drezner, Z., Turel, O., and Zerom, D. (2008), Al-Achi, A. (2019), Keldenich, T. (2021), Hodson, T. (2022), Alasmary, F. (2019).

C. Hypothesis results screenshots from the Application dashboard



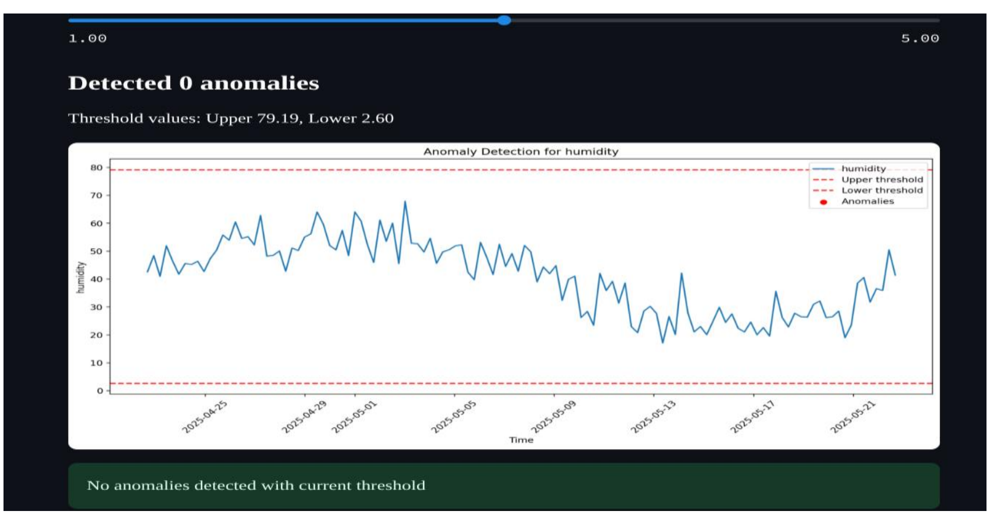




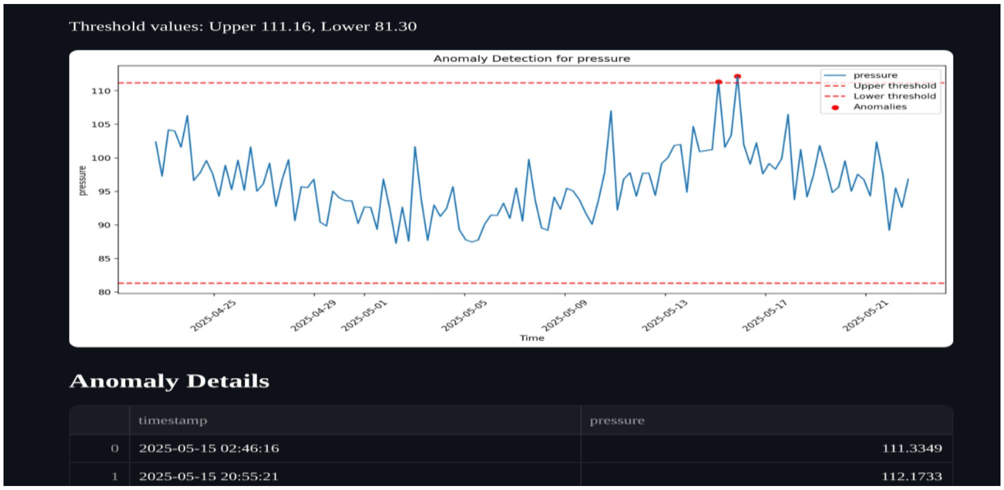


D. Anomalies detections for humidity; vibration ; pressure; temperature

4.6.1



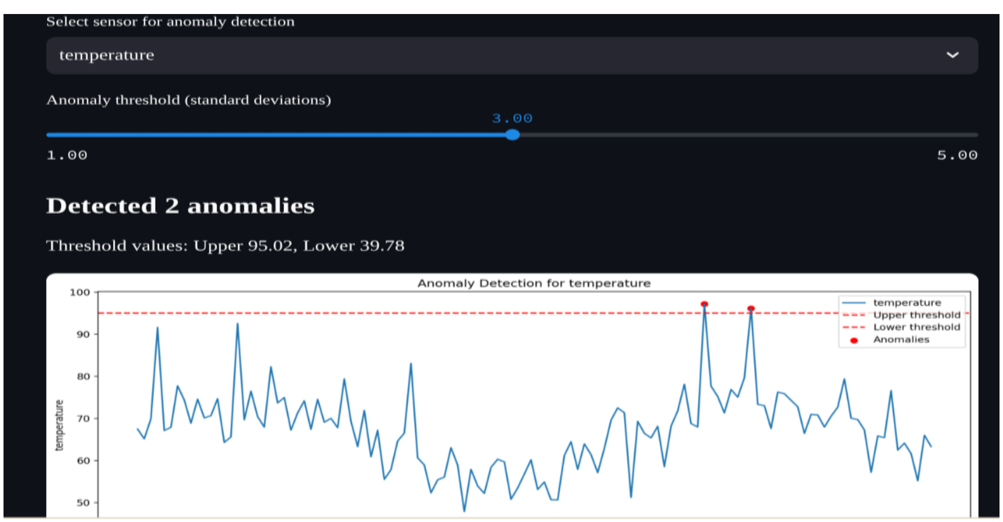
4.6.2


Threshold values: Upper 111.16, Lower 81.30
Anomaly Detection for pressure
pressure
Upper threshold
Lower threshold
Anomalies
Time
Anomaly Details
timestamp
pressure
0 2025-05-15 02:46:16 111.3349
1 2025-05-15 20:55:21 112.1733

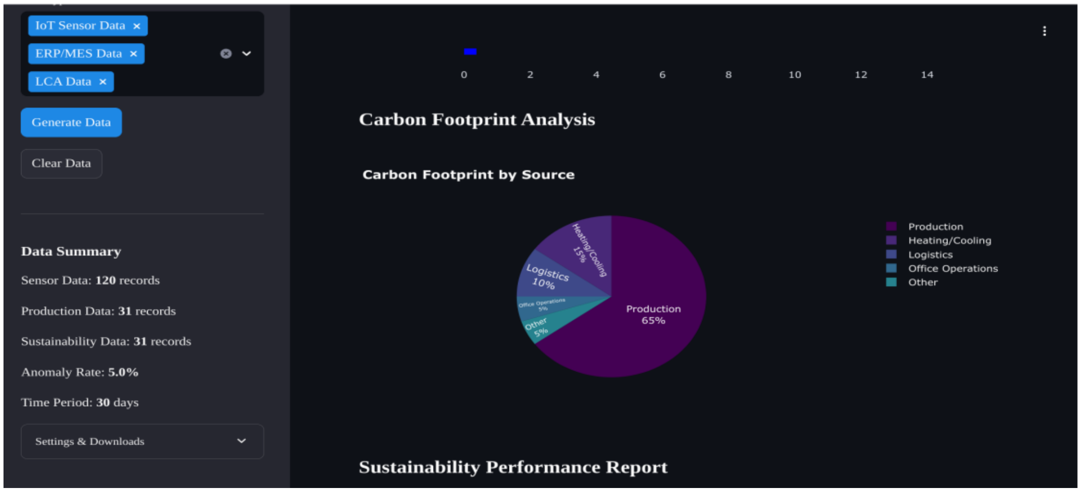
4.6.3

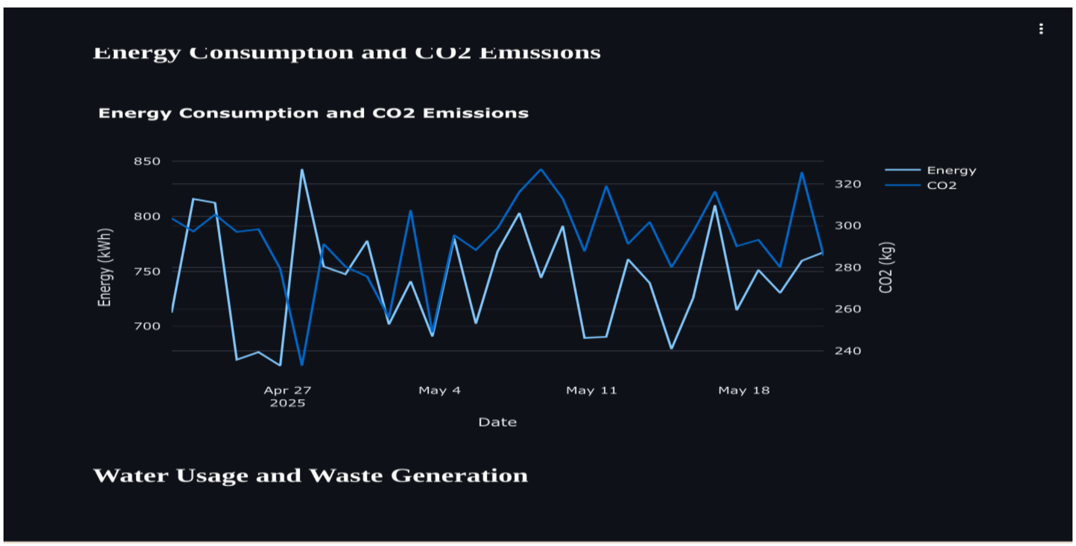

Select sensor for anomaly detection
vibration
Anomaly threshold (standard deviations)
3.00
1.00
5.00
Detected 3 anomalies
Threshold values: Upper 1.21, Lower -0.15
Anomaly Detection for vibration
vibration
Upper threshold
Lower threshold
Anomalies

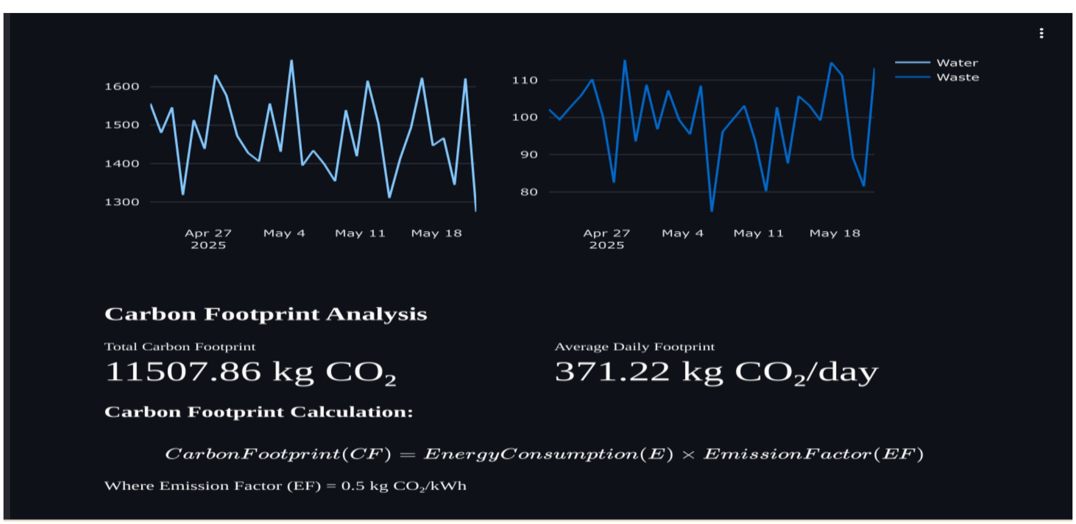
4.7.4


Select sensor for anomaly detection
temperature
Anomaly threshold (standard deviations)
3.00
1.00
5.00
Detected 2 anomalies
Threshold values: Upper 95.02, Lower 39.78
Anomaly Detection for temperature
temperature
Upper threshold
Lower threshold
Anomalies

E. Carbon Footprint

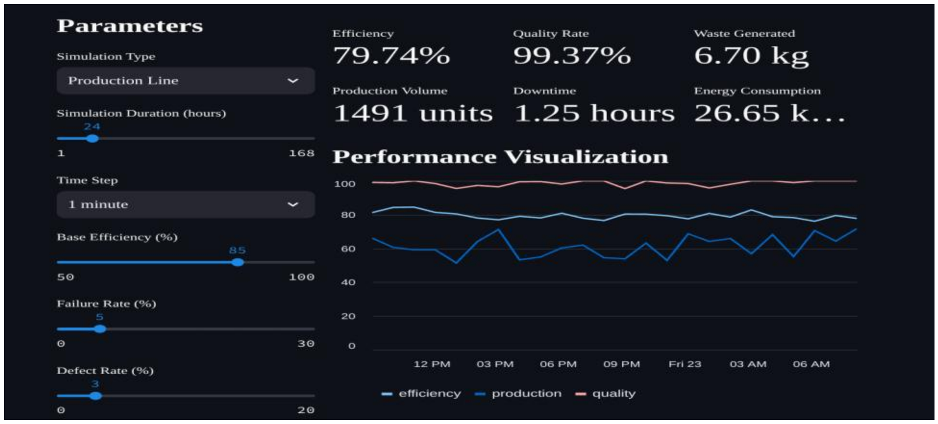




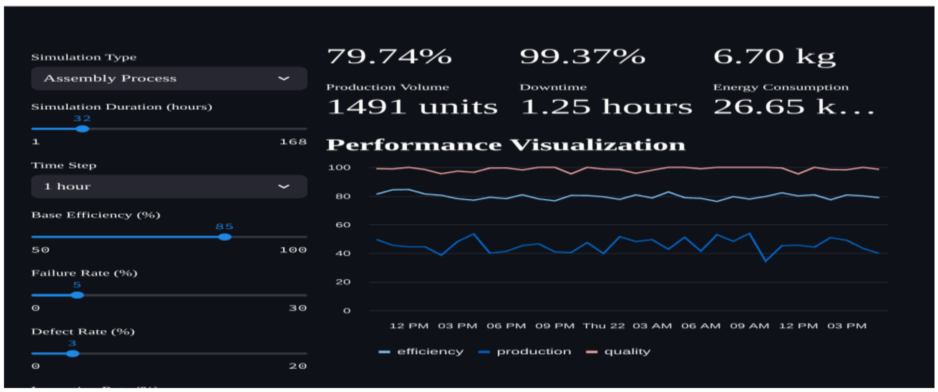


F. Analysis of Simulation Results and Performance Visualization

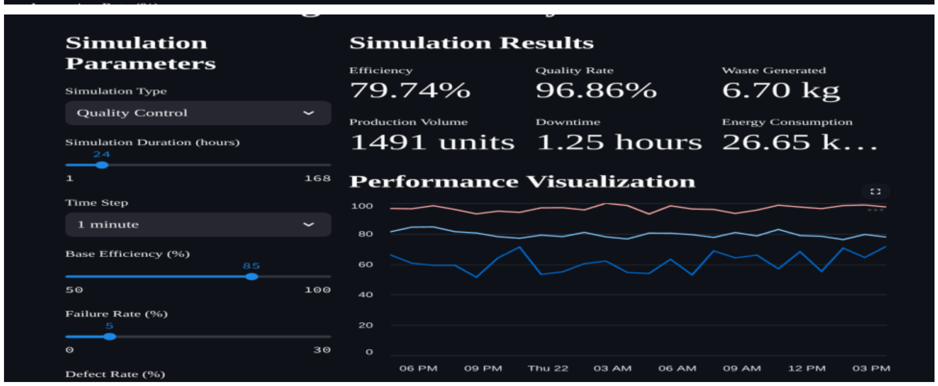
I)



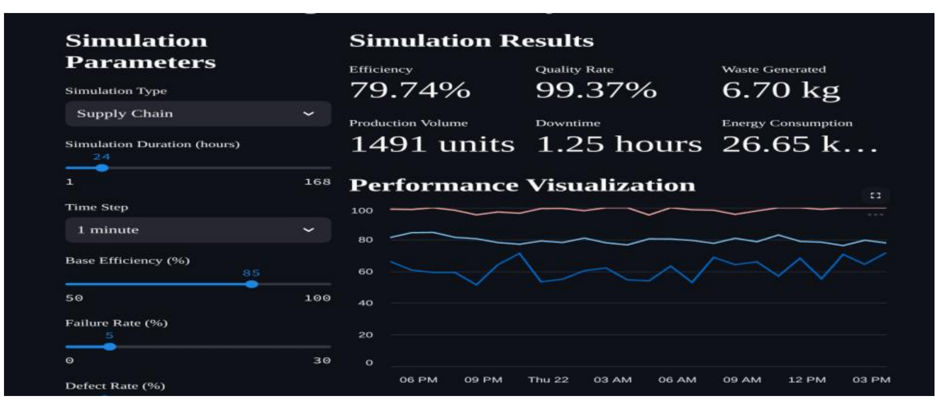
II)



III)

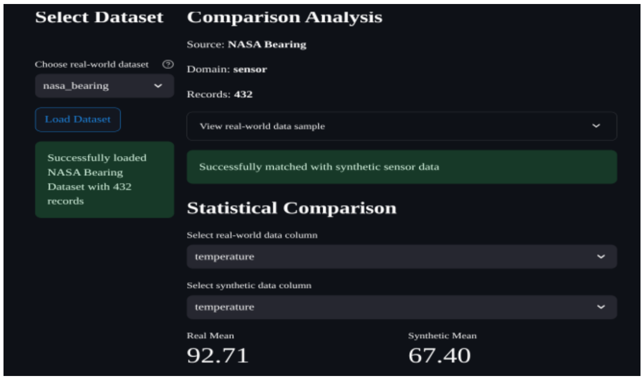


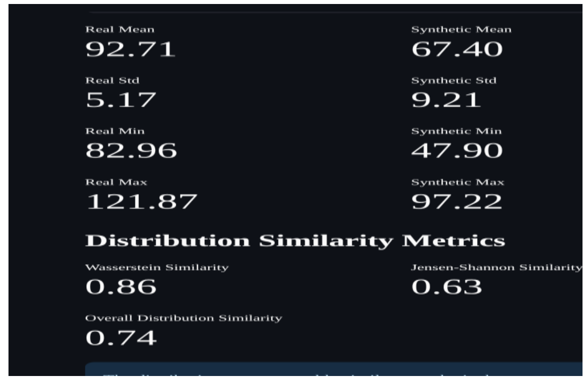
IV)

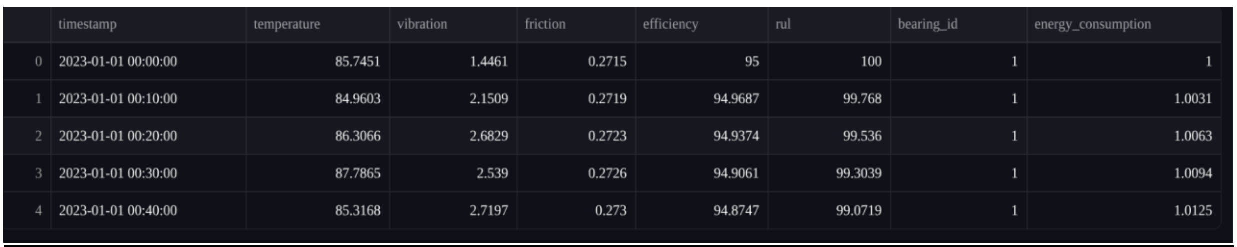


G.Analysis of Real-World vs. Synthetic Data for AI-Driven KPI Systems

a) Nasa Bearing:

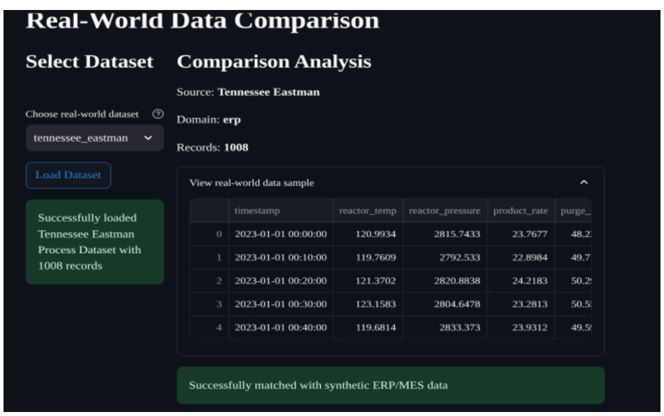






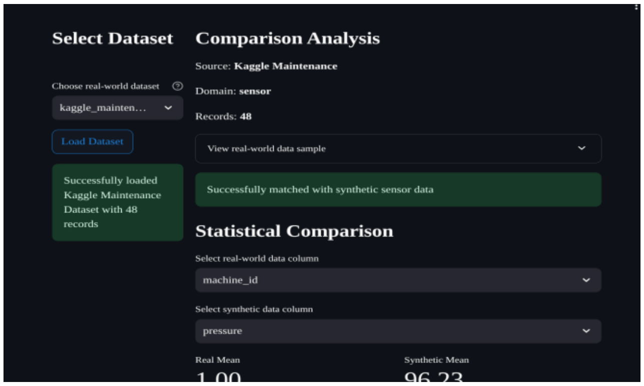
	timestamp	temperature	vibration	friction	efficiency	rul	bearing_id	energy_consumption
0	2023-01-01 00:00:00	85.7451	1.4461	0.2715	95	100	1	1
1	2023-01-01 00:10:00	84.9603	2.1509	0.2719	94.9687	99.768	1	1.0031
2	2023-01-01 00:20:00	86.3066	2.6829	0.2723	94.9374	99.536	1	1.0063
3	2023-01-01 00:30:00	87.7865	2.539	0.2726	94.9061	99.3039	1	1.0094
4	2023-01-01 00:40:00	85.3168	2.7197	0.273	94.8747	99.0719	1	1.0125

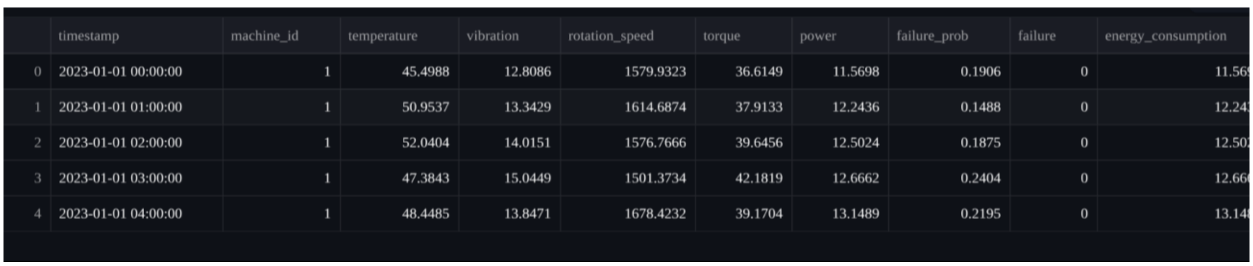
b) Tennessee Eastman



	timestamp	reactor_temp	reactor_pressure	product_rate	purge_rate	recycle_flow	feed_rate	production_volume	product_quality	efficiency	energy_consumption	quality_rate
0	2023-01-01 00:00:00	120.9934	2815.7433	23.7677	48.2303	25.7547	64.0495	86.5499	94.1889	80.5928	1340.238	91.681
1	2023-01-01 00:10:00	119.7609	2792.533	22.8984	49.7135	25.2483	62.9539	91.3895	94.9178	85.4515	1649.0138	91.4114
2	2023-01-01 00:20:00	121.3702	2820.8838	24.2183	50.2944	25.8572	63.7148	113.7718	100.8593	90.8221	1705.4515	97.4376
3	2023-01-01 00:30:00	123.1583	2804.6478	23.2813	50.5552	26.387	63.3936	110.2004	97.0609	89.6284	1654.2807	99.0687
4	2023-01-01 00:40:00	119.6814	2833.373	23.9312	49.5982	26.2551	64.214	96.3687	99.6082	85.1717	1466.4214	94.784

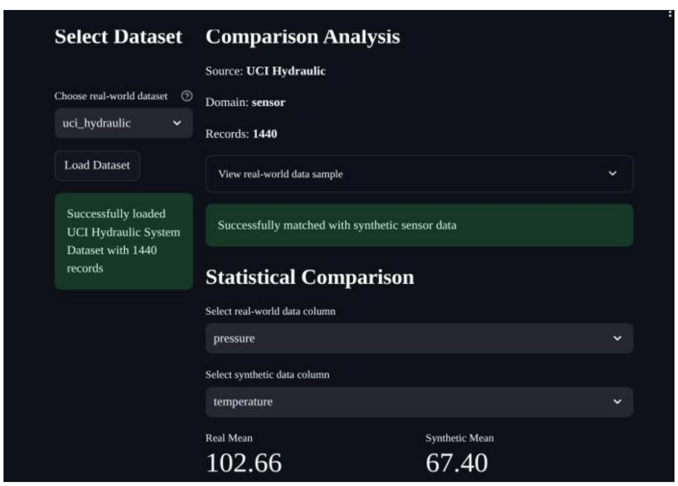
c) Kaggle Maintenance

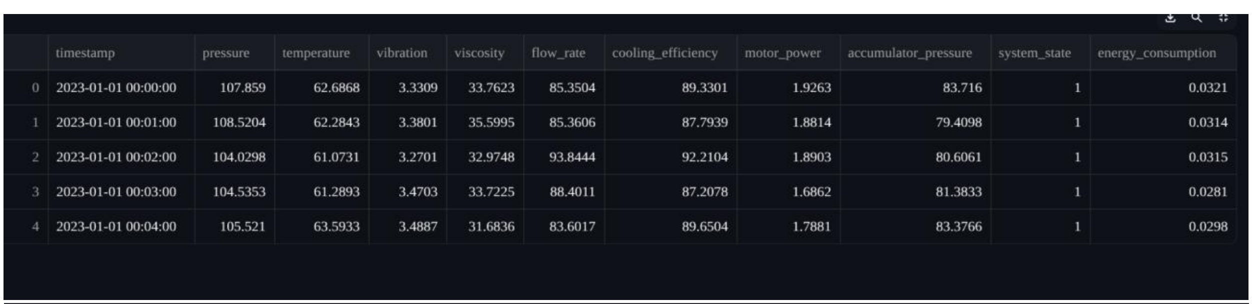




	timestamp	machine_id	temperature	vibration	rotation_speed	torque	power	failure_prob	failure	energy_consumption
0	2023-01-01 00:00:00	1	45.4988	12.8086	1579.9323	36.6149	11.5698	0.1906	0	11.56
1	2023-01-01 01:00:00	1	50.9537	13.3429	1614.6874	37.9133	12.2436	0.1488	0	12.24
2	2023-01-01 02:00:00	1	52.0404	14.0151	1576.7666	39.6456	12.5024	0.1875	0	12.50
3	2023-01-01 03:00:00	1	47.3843	15.0449	1501.3734	42.1819	12.6662	0.2404	0	12.66
4	2023-01-01 04:00:00	1	48.4485	13.8471	1678.4232	39.1704	13.1489	0.2195	0	13.14

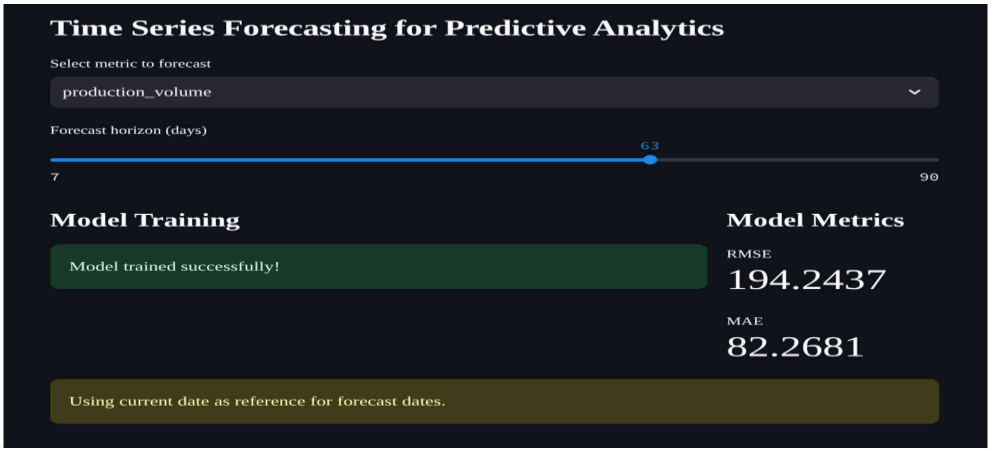
d) UCI Hydraulic System

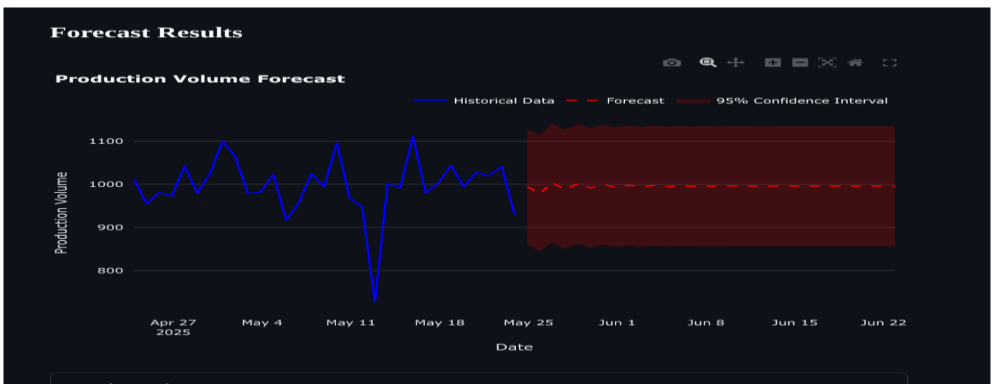


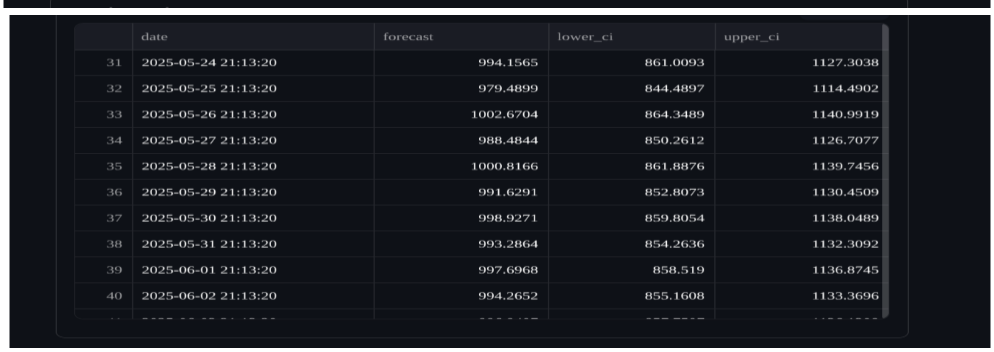


	timestamp	pressure	temperature	vibration	viscosity	flow_rate	cooling_efficiency	motor_power	accumulator_pressure	system_state	energy_consumption
0	2023-01-01 00:00:00	107.859	62.6868	3.3309	33.7623	85.3504	89.3301	1.9263	83.716	1	0.0321
1	2023-01-01 00:01:00	108.5204	62.2843	3.3801	35.5995	85.3606	87.7939	1.8814	79.4098	1	0.0314
2	2023-01-01 00:02:00	104.0298	61.0731	3.2701	32.9748	93.8444	92.2104	1.8903	80.6061	1	0.0315
3	2023-01-01 00:03:00	104.5353	61.2893	3.4703	33.7225	88.4011	87.2078	1.6862	81.3833	1	0.0281
4	2023-01-01 00:04:00	105.521	63.5933	3.4887	31.6836	83.6017	89.6504	1.7881	83.3766	1	0.0298

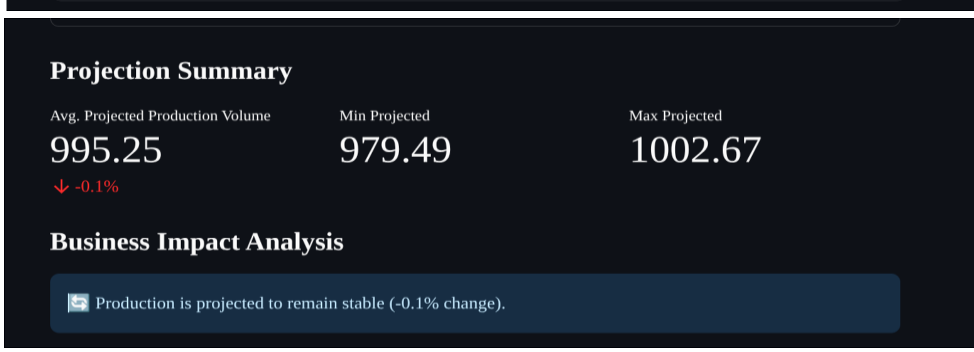
H. Analysis of Forecasting Results and Business Impact



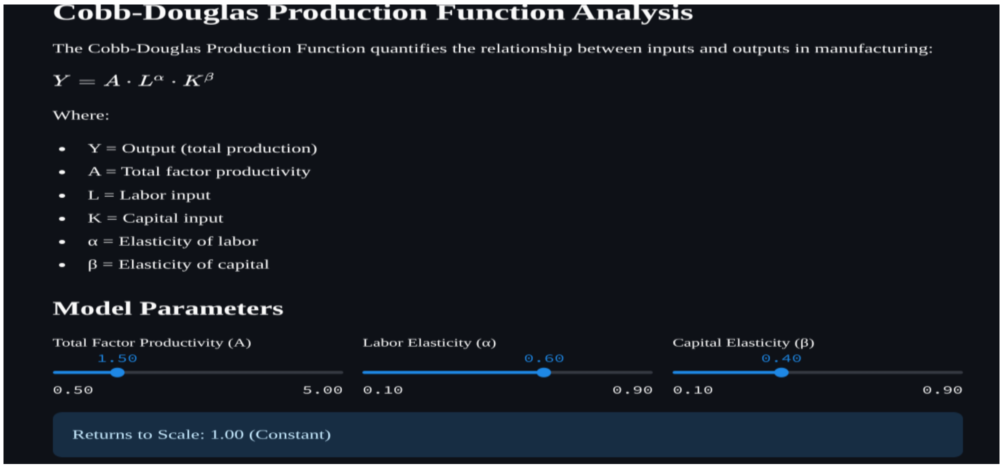


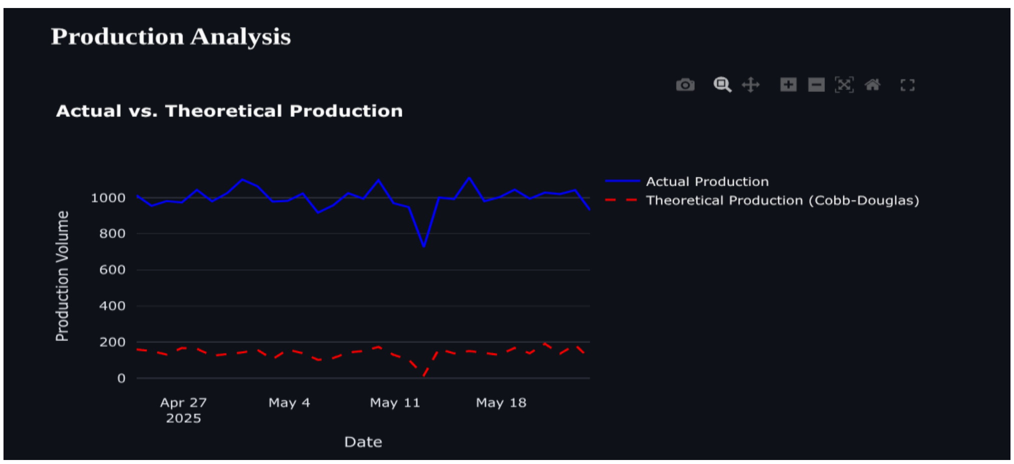


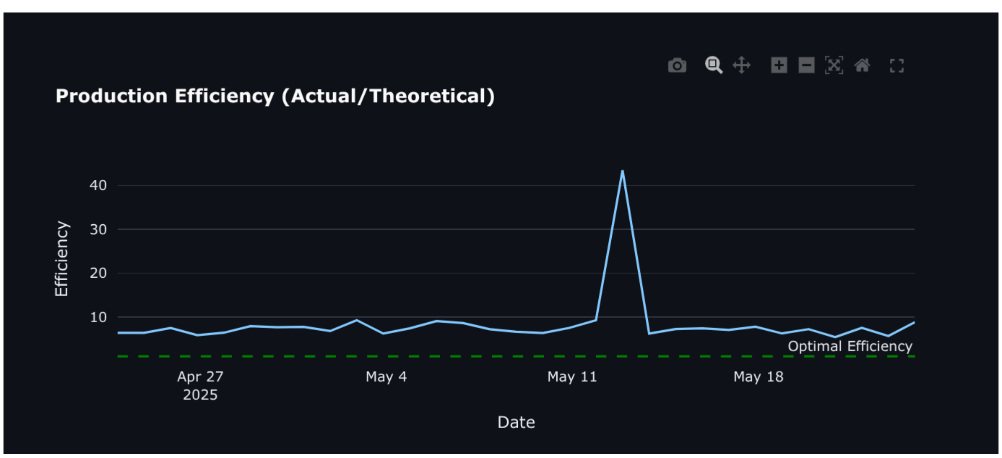
	date	forecast	lower_ci	upper_ci
31	2025-05-24 21:13:20	994.1565	861.0093	1127.3038
32	2025-05-25 21:13:20	979.4899	844.4897	1114.4902
33	2025-05-26 21:13:20	1002.6704	864.3489	1140.9919
34	2025-05-27 21:13:20	988.4844	850.2612	1126.7077
35	2025-05-28 21:13:20	1000.8166	861.8876	1139.7456
36	2025-05-29 21:13:20	991.6291	852.8073	1130.4509
37	2025-05-30 21:13:20	998.9271	859.8054	1138.0489
38	2025-05-31 21:13:20	993.2864	854.2636	1132.3092
39	2025-06-01 21:13:20	997.6968	858.519	1136.8745
40	2025-06-02 21:13:20	994.2652	855.1608	1133.3696

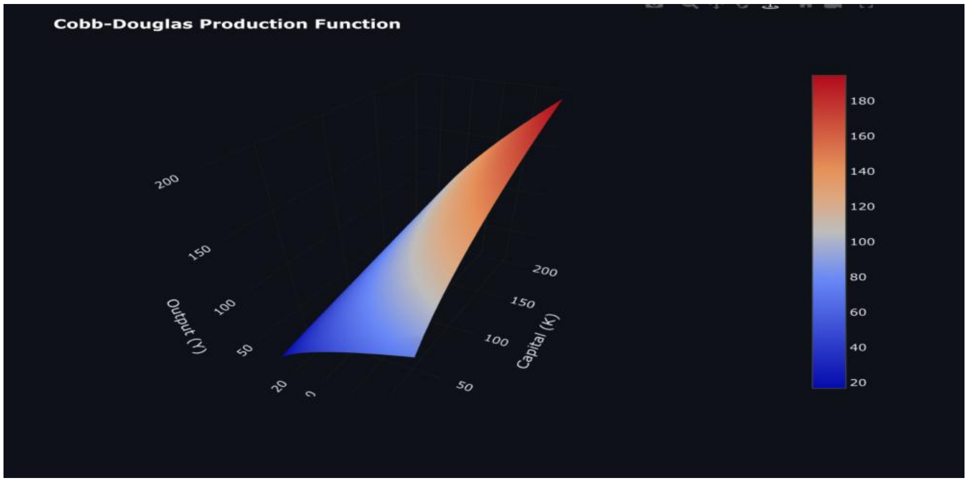


I. Analysis of production efficiency and optimization recommendations using the Cobb-Douglas Production Function.









J. Downtime analysis and Overall Equipment Effectiveness (OEE) analysis