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Research Article

An Integrated AI, IOT, and Digital Twins Framework for Engineering Optimization and Strategic Business Intelligence in the Philippines

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ABSTRACT

This study is designed and assessed an Artificial Intelligence (AI) supported Internet of Things (IoT) and Digital Twin approach for Predictive Business Intelligence, following Design Science Research (DSR). The conceptual artefact combines IoT data acquisition, Digital Twin state representation, machine-learning analytics and a Business Intelligence decision-support layer. The UCI AI4I 2020 Predictive Maintenance Dataset with 10,000 observations is used in empirical evaluation. Precision, recall, F1 score, PR AUC, ROC AUC, calibration, and confusion matrix are used to compare performance of Logistic Regression, Decision Tree, Random Forest and XGBoost for binary machine-failure prediction. The experimental results indicate that the XGBoost model performed best overall, with a precision of 0.661, recall of 0.725, F1-score of 0.692, PR-AUC of 0.660, and ROC-AUC of 0.965, thus detecting 37 out of the 51 failures in the held-out test set. In the experiment, Random Forest had the lowest Brier Score (0.022), which means it had better probability calibration. The results show the benefits of combining the machine-learning predictions, Digital Twin representation, and BI interfaces to convert operational IoT data into predictive risk data for maintenance decision making. It provides an AI-IoT-Digital Twin architecture that can be replicated and a set of empirical methods for predictive Business Intelligence.

Keywords: Artificial Intelligence (AI), Internet of Things (IoT), Digital Twin, Business Intelligence, Predictive Analytics, Predictive Maintenance, Machine Learning, Design Science Research, XGBoost, Decision Support Systems

I. INTRODUCTION

Artificial Intelligence (AI), Internet of Things (IoT), cloud computing, big data analytics, and Digital Twin (DT) technologies have driven the evolution of traditional engineering and business systems toward intelligent, connected, and data-driven systems at a very high pace. AI offers the organizations pattern recognition, prediction, classification, optimization, and automated decision support capabilities, while IoT allows for continuous data collection and transmission from physical devices, machines, infrastructure, and operational environments. AI and IoT can be combined to create what is known as Artificial Intelligence of Things (AIoT), which allows connected systems to gain active perception of the context, learn from data, reason about the operational conditions, and take intelligent action (Xu et al., 2021).

Digital Twin technology builds on this by representing a physical object, process or system in a dynamic digital environment. Digital Twins can integrate real-time sensor data, mathematical models, simulation, machine learning, and data analytics to help track current conditions and forecast system behavior. In 2020, Fuller et al. identified five key enabling technologies to be used in the development of a Digital Twin as AI, IoT, cloud computing, simulation, and data analytics. Rasheed et al. (2020) also highlighted the importance of using Digital Twins to interweave physical systems and digital representations, enabling a Digital Twins to assist in monitoring, prediction, optimization and decision-making. AI, IoT, and Digital Twin technologies are the three aspects that come together in a special way in the context of Industry 4.0. AI and IoT serve as the data provider and the intelligence for cyber-physical systems, while Digital Twins create a virtual space for the physical systems to be represented, analyzed, simulated and optimized. According to Radanliev et al., (2022) Digital Twins is an essential part of Industry 4.0 that enables the integration of AI, IoT, cyber-physical systems and information management technologies to enhance organizational resilience and operational intelligence. So the embedding of these technologies has the potential to transform organisations from traditional reactive management to predictive and prescriptive decision making.

Recent studies also provide good evidence of the potential of Digital Twins for engineering applications. Liu et al. (2021) pointed out that Digital Twin technologies can be used in the stages of product design, manufacturing, operation, maintenance and other engineering lifecycle. Digital Twins can also enable real-time monitoring and simulation, which enable organizations to test out different scenarios without having to mess with the real world. Yao et al. (2023), in a systematic review of Digital Twin applications, pinpointed its capability to help alleviate the limitations of physical experiments by allowing for virtual analysis, simulation, prediction, and optimization.

Although technology has advanced, there are a number of challenges to overcome when implementing Digital Twin systems. Based on their research Schweiger and Barth (2023) conclude that configurations of Digital Twin systems differ significantly depending on their application and that organisations should consider the level of sophistication and the capabilities they need when implementing Digital Twin systems. Previous studies also found that lack of universal reference architectures, domain dependence, security concerns, and data-sharing problems as challenges to widespread adoption of Digital Twins (Rasheed et al., 2020). These challenges highlight the need to implement a Digital Twin beyond the mere creation of a digital model, but also the need for an integrated architecture that interweaves the data, physical systems, computational intelligence, simulation, and organizational decision-making.

The Philippine context is important for the analysis on these technologies. The Philippine Development Plan (PDP) 2023-2028 places emphasis on digitalization, connectivity, technology and innovation in the economic and social transformation to be achieved. The plan also sees the rise of Industry 4.0 as an opportunity for technology-mature enterprises, and the need to digitalise and innovate to boost productivity and competitiveness (National Economic and Development Authority [NEDA], 2023). Additionally, the PDP identifies big data, analytics, digital technologies, and Industry 4.0 as opportunities that can help Philippine industries create more value and be more competitive.

The Philippine Development Plan also states that the transformation of micro, small, and medium business establishments (MSMEs) to digitalization should be accelerated as it involves over 95 percent of the country's business establishments. Improving productivity and innovation (NEDA, 2023) is identified as mechanisms through digitalization, technology adoption and automation. This national policy is an excellent opportunity for research into engineered and operational information to be used for business intelligence. But some of the factors that affect the adoption of advanced technologies in the Philippines are infrastructure availability, connectivity, technical capabilities, investment needs, interoperability, cyber security, data governance, and workforce readiness. In the Philippines, for instance, Serafica et al (2023) highlighted the need for internet and broadband access to be widely available to reap the benefits of digitalization for widespread gains. They are especially relevant when implementing IoT and Digital Twin, processes that require continuous data acquisition, communication, cloud or edge computing and real-time analytics, which rely on reliable digital infrastructure.

Moreover, the Philippine Development Plan highlights that digital technologies present business opportunities to become agile, innovative and competitive, as well as new challenges with respect to cyber security, data privacy, and firms' capacity to keep up with new technologies (NEDA, 2023). Thus, an integrated framework for the context of the Philippines should not only be based on technological performance but must also take into account organizational, economic, infrastructure, cyber security and decision making needs.

While studies have touched upon the topics of AI, IoT and Digital Twins separately and, in some cases, in combination, there is still a need for an application-specific framework that combines these technologies with engineering optimisation and strategic business intelligence. The majority of the reported Digital Twin-related research to date concentrates on engineering applications, individual assets, manufacturing systems or technological architectures. It has also been noted in the literature that the use of more comprehensive and standardized frameworks is needed which are able to integrate multiple technologies and to be used for wider organizational decision making (Rasheed et al., 2020; Radanliev et al., 2022; Yao et al., 2023).

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Therefore, this study suggests the development of Integrated AI, IoT, and Digital Twin Framework for Engineering Optimization and Strategic Business Intelligence in the Philippines. The proposed framework will aim to integrate physical engineering systems, IoT-based data collection, AI-based analysis, simulation using Digital Twins, optimization mechanisms and business intelligence into a single decision support ecosystem. The ultimate objective is to have a framework that is practical and scalable for use by organizations in the Philippines to enhance their operational efficiency and asset performance, as well as their utilization of resources, predictive ability, risk management and their strategic decision-making.

General Objective

This research seeks to design and assess an integrated Artificial Intelligence (AI), Internet of Things (IoT) and Digital Twin (DT) approach for engineering optimization and strategic business intelligence (BI) in the Philippines.

Specific Objectives

In particular, the research will seek to:

1. Evaluate and determine technological, engineering, operational, organizational and data needs, challenges and readiness factors for the integration of AI, IoT and Digital Twin (DT) technologies in selected engineering and industry applications in the Philippines.

2. Develop an integrated framework that includes real-time data collection, AI-based analysis, DT simulation, engineering optimization and business intelligence and embed it in a decision-support system.

3. For a specific engineering performance indicator (operational efficiency, resource utilization, predictive capability, reliability, cost, or process performance), etc. selected for the benefit of the student, implement and evaluate the proposed framework using an appropriate engineering or industry based case study to assess its effectiveness.

4. Check the suitability and strategic relevance of the proposed framework in a Philippine context by assessing the scalability, interoperability, usability, decision support, and contribution to strategic business intelligence and organizational decision making.

As the adoption of Internet of Things (IoT) devices, Artificial Intelligence (AI) algorithms, Cloud, Data Analytics, and Digital Twin technologies continue to grow, Philippine organizations have substantial opportunities to further enhance engineering and business performance. But, the technologies once available do not always lead to effective organizational decision making. Operational information, engineering data, asset information, financial data and strategic business indicators are often stored in various systems, leading to disjointed information landscapes. AI and IoT can be combined to develop intelligent systems that can gather, analyze, learn from, and act upon real-time data (Xu et al., 2021). These capabilities, however, can only be achieved if the Digital Twin environment is suitable, rather than just for monitoring and prediction. Digital Twin studies also show the need to integrate physical entities, virtual models, data, communication infrastructure, and analytical capabilities for the successful implementation of a DT (Fuller et al., 2020; Rasheed et al., 2020). This is exacerbated by the technological maturity, connectivity, infrastructure, organizational capability, investment capacity, and data management practices of the Philippines. While the national development agenda has acknowledged the importance of digitalization and Industry 4.0 as ways for organizations to become more productive and competitive, they still face real challenges when it comes to implementing the technologies (NEDA, 2023).

II. RELATED WORKS

2.1 Artificial Intelligence and Internet of Things Integration

The integration between AI and IoT stands as a major advancement in the field of computer science.The fusion of AI and IoT represents a significant leap in computer science. AI and IoT are among the core technologies of Industry 4.0. IoT can capture real time data from physical objects, machines, equipment and infrastructure, whereas AI can perform analysis on these data and turn them into predictions, classification, recommendations and automated decisions.

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Xu et al. (2021) studied the use of AI and IoT and Industry 4.0 and concluded that the embedding of AI in an IoT environment can foster innovation and digital transformation. They point out how the fields of sensing, connectivity, computation, machine learning, and intelligent decision making come together in Industry 4.0 systems. AI-driven IoT can thus transition from capturing data to learning from operation conditions and be able to assist with intelligent responses. This is especially important in engineering applications where significant amounts of sensor data are collected and analysed regularly to detect any abnormal state, forecast equipment operation and enhance the processes. Similarly, Rasheed et al. (2020) revealed that AI and IoT are important enabling technologies for Digital Twin environments. The Digital Twin concept, according to their review, is based on the integration of physical and virtual systems based on data exchange and modelling. IoT offers the physical-virtual linkage of data, and AI and analytical models can use the data to make predictions and optimizations.

El-Haik et al. (2021) conducted a wider review on AI and IoT in Industry 4.0 and highlighted that the combination of AI and IoT would result in an intelligent cyber-physical system. The authors observed that while these technologies bring numerous opportunities for automation and efficiencies, they also pose threats to cybersecurity, data management, interoperability, and system complexity. These challenges are especially critical when there are multiple engineering systems and organizational information systems whose data must be shared. To explore the relationship between AI, IoT, cyber-physical systems, and Digital Twins, Radanliev et al. (2022) continued their study. They define Digital Twins as a digital representation of a physical object or process in real time, and highlight the close relationship between AI, IoT, information management and Industry 4.0. They find that the value of these technologies is not just in individual capabilities, but also from their embrace and connection within a wider set of technological and organizational ecosystems.

The literature thus concludes that IoT is the data infrastructure, AI is intelligence, and Digital Twin technology is virtual representation and simulation. This connection helps provide a theoretical basis for the proposed integrated framework. A digital twin is a digital representation of a physical system.A digital twin is a virtual representation of a real-world system. Digital Twin has emerged as one of the most prominent technology related to Industry 4.0. While there are several different definitions of Digital Twin, most studies define it as the digital representation of a real object or process, with the data connection being maintained in some form.

2.2 Digital Twin Technology and Its Architectural Foundations

An extensive review of Digital Twin technologies, challenges and enabling technologies was done by Fuller et al. (2020). They found five key technologies that will enable the use of Digital Twin: AI, IoT, cloud computing, simulation, and data analytics. The authors highlighted the use of Digital Twins in industrial applications, healthcare, smart cities and other complex systems. They did, however, find that challenges related to interoperability, data management, security and integration of multiple enabling technologies existed as well. These results prove that a Digital Twin should be considered as a technological ecosystem, not just a 3D digital model. The concept of Digital Twins has been systematically reviewed in the literature by Jones et al. (2020) and a thorough classification of the concept is formulated. They reviewed 92 publications and found 13 characteristics of Digital Twins such as the physical entity, virtual entity, physical and virtual environments, state, realization, metrology, twinning and twinning rate, physical-twin, virtual-to-physical connection, physical and virtual processes. In a significant way, the study revealed gaps in research related to technical implementation, fidelity of Digital Twin, data ownership, lifecyclisation applications, and integration between virtual entities.

It is crucial for the proposed study since it illustrates that beyond a mere digital representation, an effective Digital Twin framework needs to be systematic. It needs to provide ways of obtaining information about the physical system, synchronizing the data with a virtual system, analysing the data, and then transmitting information or control actions back to the physical system. Melesse et al. (2021) performed a systematic review of 41 publications for Digital Twin models in Industrial Operations. They found important applications in production and predictive maintenance, and continued challenges with the implementation of Digital Twin. Based on their findings, they believe Digital Twins could be a useful engineering tool for the enhancement of operational performance and maintenance activities.

Liu et al. (2023) have chosen to study Digital Twin physical entities, virtual models, twin data, and applications in a systematic way. Their studies included techniques for the acquisition of physical information, the construction of virtual models, the acquisition of the data in the virtual model, and the exchange of data between the virtual model and the physical model. This is especially significant to the proposed research, as it demands the incorporation of physical engineering assets, IoT-based data acquisition, virtual models and analytical mechanisms. Yao et al. (2023) also carried out a systematic review of the Digital Twin technologies and applications. The authors identified Digital Twins as technologies that can overcome the limitations of time, space, cost, and security and enable the analysis, simulation, and optimization of physical entities, including the creation of a digital representation of them. As shown in their review, Digital Twins are increasingly being applied in the fields of engineering and industry.

These studies together lay the conceptual and architectural groundwork for Digital Twin. They also show that integration with intelligent analytics, real-time synchronisation, model fidelity, data integration and interoperability are still great research challenges.

2.3 Digital Twins for Engineering Optimization

One of the most important applications of Digital Twin technology is engineering optimization. Traditional engineering optimization process may need physical experimentations, historical data or mathematical modeling. This can be costly, time-consuming, and not be able to model rapidly changing operational conditions. Rasheed et al. (2020) highlighted the Digital Twins have the potential to combine data-driven and physics-based models to assist in monitoring, prediction and optimisation. Real-time data from IoT devices with virtual models is a chance to test the operation of the system in various scenarios without changing the physics of the system.

Thelen et al. (2022) analyzed Digital Twin modeling, enabling technologies, uncertainty quantification and optimization. Key points from their review included the possibilities for Digital Twins in process design, quality control, health monitoring, decision making and policy making. The authors also stated uncertainty quantification and optimization are key to the future of the Digital Twin. They can play an important role in the research proposed in this project, as in engineering optimization one must consider not only the states that are expected to occur in the system but also the uncertainty in data, models and in operating conditions. Zeb et al. (2021) discussed next generation wireless networks and computational intelligence at the intersection of industrial Digital Twins. They defined Digital Twins as systems that leverage communication technologies, machine learning, AI, cloud computing, edge computing and data analysis to monitor, analyze, predict and optimize industrial processes. This highlights the need for communication and computing infrastructure in real-time Digital Twin applications.

One of the most significant applications is predictive maintenance. Van Dinter, Tekinerdogan and Catal (2022) performed a systematic literature review of predictive maintenance with Digital Twins and reviewed 42 primary studies. Their review concluded that Digital Twins can be used to offer real-time representations of the physical machines and generate information of asset degradation which can be used by predictive maintenance algorithms. The authors noted however, computational burden, data variety and model complexity as key challenges. The results show that Digital Twins can change the engineering maintenance from reactive to predictive. An integrated IoT-AI-Digital Twin system doesn't have to wait for equipment failure to track the equipment's state of health, recognize degradation trends, predict the equipment's future health, and enable maintenance decisions.

Wang et al. (2023) also examined the research of Digital Twin technology in the context of predictive maintenance and pointed out the significance of real-time perception, high-fidelity model, data fusion and simulation predictions. They have suggested a reference architecture comprising data collection, state judgment and service decision-making layers. The results are highly favorable for the second and third goals of the proposed study, namely the development of an integrated architecture for processing IoT data, prediction by AI, simulation using Digital Twin, and engineering optimization.

2.4. AI and Digital Twins

AI is an essential component of a Digital Twin environment. While a conventional Digital Twin could give a digital representation and picture of any physical system, AI could truly enhance its analytical and predictive power.

Tao et al. (2021) analysed the application of AI-based Digital Twins in Industry 4.0 in the context of smart manufacturing and advanced robotics. They found AI and Digital Twin technologies to be significant enabling technologies for Industry 4.0 and highlighted their potential for intelligent manufacturing, process optimization and automation.

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Radanliev et al. (2022) also defined the synergy of the three technologies: AI, IoT, and cyber-physical systems and Digital Twins to create more intelligent and resilient industrial environments. Together, it enables Digital Twins to move beyond the passive digital representation to become predictive and decision-supportive analytical systems.

There are but AI-enabled Digital Twins come with challenges, too. For AI models to be effective, they need ample and quality data, and for Digital Twins to be effective, they need to be synced between the real and virtual world. Prediction and optimization outcomes can be adversely impacted by poor sensor data, missing information, model uncertainty, computational constraints and inadequate system integration.

This implies that the proposed framework should not only combine AI algorithms and Digital Twins, but should also create a data-to-decision pipeline, where data quality, model validation, model synchronization, model uncertainty, and decision usefulness are explicitly taken into account.

2.5. Concepts and applications of business intelligence and industry 4.0.

Engineering optimization alone does not give enough value to an organization if it is not linked with strategic business goals. Business Intelligence (BI) offers tools to transform data from operational and organizational systems into information and insights to guide decision making.

Eggert and Alberts (2020) explored the evolution of Business Intelligence and Analytics (BI&A) and found a third wave of BI&A which sees more use of unstructured and sensor generated data. The systematic review of 75 research papers they conducted showed the growing importance of sensor and data intensive technology in BI&A. The development is directly applicable to the engineering surroundings for IOT, as sensors can produce a massive amount of operational data that can be integrated in to business intelligence systems. The authors Silva, Cortez, Pereira and Pilastri (2021) performed a systematic literature review on Business Analytics in Industry 4.0, with a sample of 169 publications. They divided analytics applications into three categories: descriptive, predictive and prescriptive. Through their review, they have found that business analytics in the context of Industry 4.0 is not limited to reporting historical business data but also includes predictive modeling and optimization.

This is a crucial step in the proposed study. Descriptive analytics can help answer the questions of what happened in an engineering system; predictive analytics can help answer what will happen; and prescriptive analytics can help answer what should be done. All three levels can be potentially supported by an integrated AI-IoT-Digital Twin framework.

Tavera Romero et al. (2021) explored the concept of Business Intelligence in the context of Industry 4.0, and noted that new digital technologies are revolutionizing business models and empowering organizations to react quickly to the changing market dynamics. This work provides a foundation for the discussion on the integration of BI in Industry 4.0 architectures instead of only as a reporting system. Yalcin, Kilic, and Delen (2022) discussed the applications of multi-criteria decision making methods in Business Analytics. They highlighted that business analytics can reveal valuable information, aid in decision making and help in strategic planning when considering multiple criteria and constraints, while multi-criteria approaches can help organizations evaluate multiple alternatives when there are multiple objectives.

However, this is of specific interest for engineering optimization, as multiple competing objectives are often used when making engineering decisions. For instance, an organization could be looking to balance equipment reliability, energy use, production capacity, maintenance cost, environmental impact and customer requirements. Therefore, the suggested structure should not only take into account optimization from a technical point of view, but also optimization from a business perspective of the engineering decisions.

2.6 IoT Data and Business Intelligence

The aspect of IoT and Business Intelligence is another crucial aspect of the proposed research. IoT systems can produce large volumes, high velocity, and diverse data, but the value of these data depends on the capacity of organizations to turn them into actionable information.

A systematic review of IoT data visualization for business intelligence surveyed 237 publications and provided for four major research areas: technology infrastructure, case examples, end-user experience, and big-data tools. The

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study showed that the use of IoT data for BI processes is becoming more and more significant, and there are still challenges, such as data utilization and technological infrastructure (IoT Data Visualization for Business Intelligence, 2022). IoT offers a way to capture the information generated in real-time from physical systems. AI gives analytical intelligence to help identify patterns, make predictions, and detect anomalies. Digital Twin technology creates a virtual dynamic model of the physical system, allowing the integration of various information and models and simulations. Engineering optimization takes advantage of these features to enhance system performance, reliability, efficiency, maintenance and resource utilization. Lastly, Business Intelligence transforms engineering and operational outputs into business information that can be used for strategic decisions.

All individual components are strongly supported in the literature. Fuller et al. (2020), Jones et al. (2020), Melesse et al. (2021), Liu et al. (2023), and Yao et al. (2023) provide theoretical and technological underpinnings of Digital Twins. The use of AI and IoT in intelligent cyber-physical systems has been highlighted by the works of Rasheed et al. (2020) and Radanliev et al. (2022), and other AI-IoT studies. The studies by Van Dinter et al. (2022) and other predictive-maintenance studies show the engineering potential of Digital Twins for monitoring, prediction and maintenance optimisation. At the same time, Eggert and Alberts (2020), Silva et al. (2021), Tavera Romero et al. (2021), and Yalcin et al. (2022) indicate how Business Intelligence has grown beyond reporting to more sophisticated forms of analytics, predictive modelling, optimisation and decision support.

Table 1. Review of Empirical Studies in Digital Twin, IOT and IO in Business Intelligence

Author/Year	**Focus**	**Major Contribution**	**Relevance to Proposed Study**
Fuller et al. (2020)	Digital Twin technologies	Identified enabling technologies, applications, and challenges	Provides foundation for DT architecture
Jones et al. (2020)	Digital Twin SLR	Characterized DT concepts and identified research gaps	Supports DT conceptual framework
Rasheed et al. (2020)	DT modeling	Examined values, challenges, modeling, and enabling technologies	Supports integration of models and data
Eggert & Alberts (2020)	BI & Analytics	Developed taxonomy and research agenda for BI&A 3.0	Supports strategic analytics component
Melesse et al. (2021)	Industrial DT	Reviewed DT applications in industrial operations	Supports engineering applications
Radanliev et al. (2022)	AI, IoT, DT	Integrated AI and IoT cyber-physical systems with DT	Strong foundation for AI-IoT-DT integration
Silva et al. (2021)	Business Analytics	Systematic review of 169 Industry 4.0 studies	Supports descriptive, predictive, and prescriptive analytics
Tavera Romero et al. (2021)	BI and Industry 4.0	Examined evolution of BI under Industry 4.0	Supports business intelligence integration
Van Dinter et al. (2022)	DT predictive maintenance	SLR of 42 studies	Supports predictive engineering optimization
Yalcin et al. (2022)	Business Analytics	Reviewed analytics and multi-criteria decision-making	Supports strategic optimization

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Liu et al. (2023)	DT systematic review	Reviewed physical entities, virtual models, twin data, and applications	Supports integrated DT architecture
Yao et al. (2023)	DT systematic review	Reviewed DT technologies and applications	Establishes current research landscape
Serafica et al. (2023)	Philippine digital infrastructure	Reviewed broadband and digitalization challenges	Provides Philippine infrastructure context
NEDA (2023)	Philippine Industry 4.0	Identified digitalization, Industry 4.0, AI, and technology adoption priorities	Provides national policy context

But this synthesis leaves a major research gap. The existing research mainly focuses on the individual technological relations or specific application areas. Digital Twin studies are often on engineering assets, production, maintenance or manufacturing. The research area of AI-IoT is the smart sensing and cyber physical systems. The focus of Business Intelligence research is mainly on analytics and business decision making. Comparatively, less research has created an integrated architecture that brings those components from physical engineering systems, through to strategic business intelligence. Especially in the Philippines. There are plenty of technical foundations in the existing international research and there is policy literature on the importance of digitalization and Industry 4.0 in the Philippines. But the evidence of a comprehensive, empirically tested framework of AI-IoT-Digital Twin that integrates engineering optimization with strategic business intelligence in the context of Philippine technological landscape and organizational environment is still limited.

III. MATERIALS AND METHODS

This study was conducted using a Design Science Research (DSR) research design methodology in its research design development, expert evaluation, Delphi validation and quantitative performance assessment, as well as following a Systematic Literature Review (SLR), mixed-methods research, case study, prototype. This combination of methods was suitable since the study was not only a description or explanation of the relationship between Artificial Intelligence (AI), Internet of Things (IoT), Digital Twin (DT), engineering optimization and Business Intelligence (BI). Instead, it aimed at designing, developing, demonstrating, evaluating, and validate an integrated technological framework that will meet the need for engineering and strategic decision making needs in the Philippine context. This study has then used an integrated Design Science Research (DSR) and Machine Learning (ML) approach to develop, implement and validate an AI-, Internet of Things (IoT)-, and Digital Twin-based system for engineering optimisation and strategic business intelligence in the context of the Philippines. The overall methodological framework for designing and validating the proposed technological artifact will be based on Design Science Research, and the computational mechanism for the predictive analytics, optimization, anomaly detection and decision support will be based on machine learning experimentation with RapidMiner AI Studio.

The methodology seems suitable as the study doesn't involve the relationship between variables. It aims to develop and test a meaningful framework that can transform real-time & historical engineering data into operational & strategic intelligence. The methodological approach used was Design Science Research (DSR) due to the nature of the main result of the study, which is a technological artefact (ISA). Peffers et al. (2007) presented their Design Science Research Methodology which involves the following steps: problem identification and motivation, definition of objectives, design and development, demonstration, evaluation, and communication. The stages gave methodological justifications for the development and evaluation of the proposed Integrated AI, IoT and Digital Twin Framework for Engineering Optimization and Strategic Business Intelligence in the Philippines. The methodology was modified to suit the engineering, technological, organizational and strategic aspects of the study. The research was conducted in an iterative manner, starting with the identification of engineering and business intelligence problems, then a systematic review of the existing knowledge, and a study of the technological and organizational requirements. The results of these findings were used to design and develop the framework and prototype. The artifact was then presented to a selected engineering or industrial case, evaluated technically and empirically and

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validated by experts. The results of the evaluation and validation process were used to modify the framework before formalization.

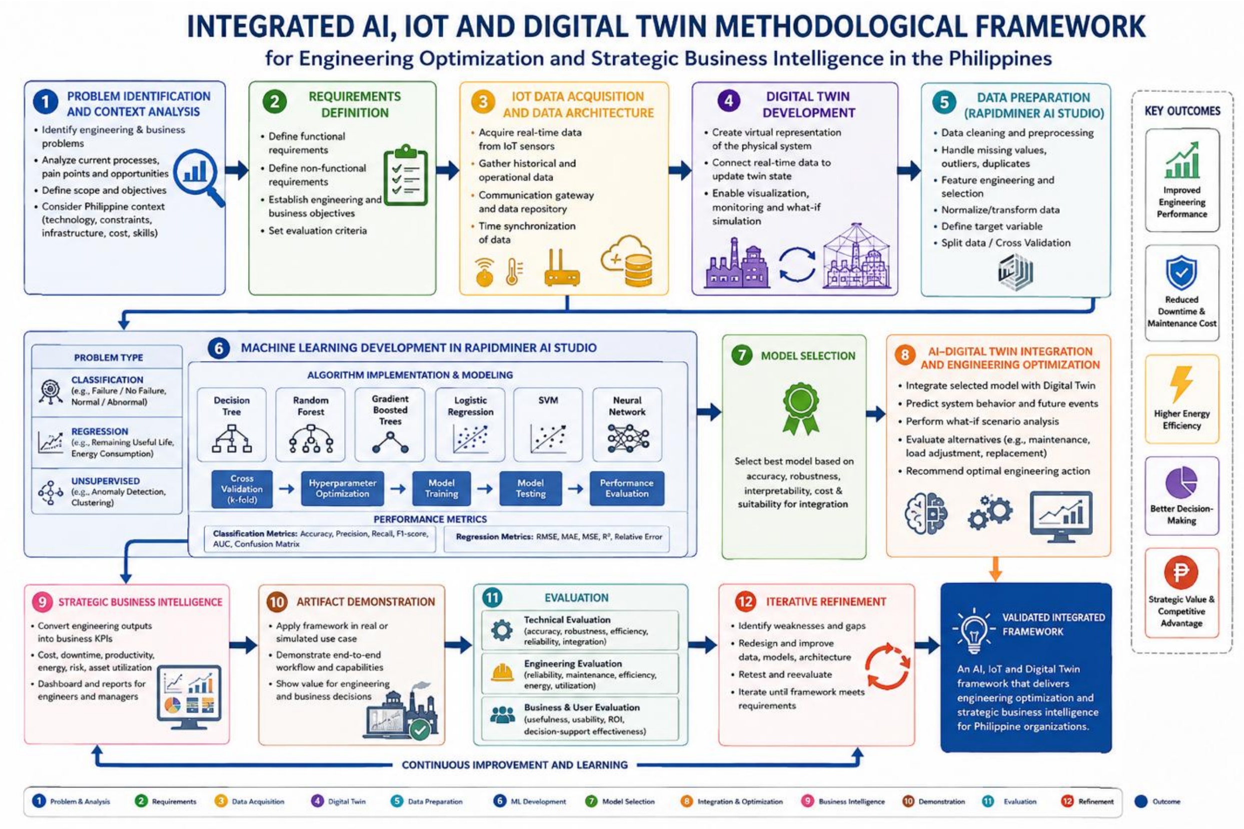

Figure 1. Conceptual Framework of the Study

The proposed methodological framework as shown in Figure 1 is based on Design Science Research (DSR) and Machine Learning (ML) to develop, implement and evaluate an AI, Internet of Things (IoT) and Digital Twin-based system for Engineering Optimization and Strategic Business Intelligence in the Philippines. Design Science Research is the overall research methodology because the study not only seeks to analyze an existing engineering problem, but also to design, develop, demonstrate and evaluate a technological artifact that can offer practical solutions to engineering and organizational problems. Machine learning implementation in Rapidminer is the key analytical process in the DSR that converts engineering or operational data into predictive and actionable intelligence.

The framework starts with Problem Identification and Context Analysis in which particular challenges in the engineering and business are identified. The focus of this stage is on reviewing current operating procedures, equipment performance, maintenance practices, equipment use, energy use, production productivity, and other engineering issues. It also helps set the Philippine context, taking into account the technological infrastructure, organizational capacity, costs, and competencies of the workforce, and the extent of digital transformation in participating organizations. The identified problems are the foundation for understanding how AI, IoT and Digital Twin technology can support engineering improvement and strategic decision-making.

The second phase is Requirements Definition in which functional and non-functional requirements of the proposed system are taken. The functional requirements are what the framework is supposed to do, which includes collecting operational data, monitoring equipment conditions, predicting failures or equipment performance, doing what-if analysis and generating management level information. Non-functional requirements include reliability, scalability, inter-operability, usability, security, model accuracy, computational efficiency and feasibility. These are the requirements that will also be used as evaluation criteria in the later stages of the Design Science Research process.

The third stage is IoT Data Acquisition and Data Architecture. Real-time and historical engineering data are collected using IoT devices, sensors, controllers, databases and existing operational information systems. These variables can

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vary based on the engineering application being selected, such as temperature, vibration, pressure, voltage, electrical current, equipment operating hours, energy consumption, equipment production rate, equipment status, machine downtime, equipment maintenance history and equipment utilization. The IoT architecture is the link between the physical engineering environment and the digital analytical environment, which allow the data to be sent continuously or periodically to the proposed system.

In the fourth stage, Digital Twin Development, the focus is on the development of the Digital Twin. A Digital Twin is a virtual model of the selected physical engineering asset, process, facility, or system. The updated real time and historical data from the IoT layer is used to update the state of the virtual model. This enables the framework to be applied to actual operating conditions, and facilitates the visualization, monitoring, analysis, testing of scenarios and prediction. The Digital Twin is thus the connecting point in the framework between the physical engineering system and the AI-driven analysis part.

The fifth step is the Data Preparation by means of RapidMiner AI Studio after data acquisition and the creation of Digital Twins. Raw IoT and operational data are transformed to benefit their quality and usability in machine learning. Data preprocessing phase involves handling of missing data, removal of duplicate data records, detection and treatment of outliers, feature transformation, normalization of numerical values, selection of relevant attributes and engineering features creation. These could include moving averages, equipment use metrics, temperature differences, running hours, failure rates, maintenance cycles, and energy efficiency measures. The target variable is then determined based on the engineering problem, such as equipment failure, abnormal condition, remaining useful life, energy use, production output or operational efficiency.

The sixth step is to develop and implement machine learning concepts in RapidMiner AI Studio. Several algorithms are created and evaluated rather than a single predictive method is used. For classification problems, like predicting equipment failure or whether the operating condition is normal or abnormal, algorithms can be used as Decision Tree, Random Forest, Gradient Boosted Trees, Logistic Regression, Support Vector Machine, and Neural Networks. If a regression problem, like prediction of energy consumption, production output, downtime duration or remaining useful life, is to be solved, the appropriate regression algorithm within the machine learning field is implemented. In the absence of labelled historical data, unsupervised learning techniques can also be applied to anomaly detection or clustering.

Cross-validation, model training, model testing, hyperparameter optimization, and evaluation of model performance are all included in model development. The accuracy, precision, recall, F1 score, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R2) can be used to compare classification models, and mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) are used to evaluate regression models. For time-dependent IoT datasets, chronological validation may be used to prevent information from future observations from being unintentionally introduced into model training.

The seventh stage is called Model Selection. The machine learning algorithm with the best overall performance is chosen for implementation in the framework. They are not selected just for predicting accuracy. Other factors such as robustness, interpretability, computational efficiency, consequences of false alarms, engineering relevance and suitability for Digital Twin integration are taken into account. This will make sure that the chosen model is statistically sound and also of practical value for an engineering environment.

The eighth stage involves embedding the machine learning model that was selected in the Digital Twin to develop an AI Digital Twin for Engineering Optimization. Real-time or historical IoT measurements update the Digital Twin and the machine learning model forecasts future conditions of the system, failures, energy consumption, operational performance, etc. These forecasts can then be used to aid what-if analysis and comparison of possible engineering options. The system, for instance, might determine that equipment can continue to operate as it is, or that it should operate at some less-than-maximum load, or that it should undergo some preventive maintenance, or that a component should be replaced. The goal is to determine a suitable engineering solution that meets the balance of reliability, efficiency, safety, productivity, resource use and cost.

The 9th stage takes the Technical outputs further into Strategic Business Intelligence. Engineering predictions and optimisation results are converted into indicators which can be understood and used by managers and organisational

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decision makers. These can range from future maintenance budgets, maintenance downtime, energy consumption, production efficiency, asset usage, operating risks, savings, to ROI. This is an important link between engineering analytics and organizational strategy as well, because the impact on technical performance can be measured based on the financial and operational impact.

The framework thus contains multiple levels of intelligence. Descriptive and operational intelligence are used to identify what is going on in the engineering system. Predictive intelligence: this is based on machine learning models and what the machine is likely to do in the future. Prescriptive intelligence is the ability to determine the engineering actions that could lead to better outcomes. Finally, strategic business intelligence helps to understand how these engineering actions might affect organization costs, productivity, risks, competitiveness, and long-term decision making.

In Design Science Research, Artifact Demonstration is a significant part of the 10th stage. The developed framework is used for a selected engineering case, prototype, experimental environment, industrial dataset or simulated scenario. The demonstration aims to test if the whole process, from the acquisition of IoT data to updating the Digital Twin, generation of machine learning predictions, engineering optimization and business intelligence can be performed as an integrated system. This demonstrates the artifact's useable potential.

The 11th stage is a multi-dimensional assessment of the created artifact. Technical evaluation considers predictive accuracy, robustness of the model, reliability of the system, processing efficiency, and integration capability. Engineering evaluation includes the enhancement of equipment reliability, maintenance planning, including energy efficiency, productivity, equipment utilization, and operational performance. Business/ user evaluation focuses on the usefulness, usability, cost considerations, effectiveness of decision support, scalability, feasibility, and return on investment. Engineers, managers, IT professionals, data analysts and other experts may be involved in the review of the framework where applicable.

Lastly, the twelfth stage is Iterative Refinement as in the cyclical process of Design Science Research. The findings of model testing, engineering assessment, business analysis, and expert input are utilized to determine the weaknesses and opportunities for improvement. Data quality problems can involve further data processing or feature engineering, inadequate model performance can lead to algorithm tuning or switching to an alternative model, Digital Twin synchronization problems can lead to modifications of the architecture, and limited managerial usefulness can lead to modifications of selected business KPIs or modifications of the dashboard's design. The framework is then redesigned, retesting and reevaluation is done until the technical, engineering and business requirements are met satisfactorily.

It is through this seamless process that IoT acts as the source of real-time and historical data, while the Digital Twin serves as the virtual representation and simulation environment, RapidMiner AI Studio delivers the machine learning and predictive analytics, engineering optimization translates the predictions into technical recommendations for action, and strategic business intelligence translates the technical recommendations into information for management purposes. Design Science Research integrates these elements by offering a systematic process for designing, demonstrating, evaluating and revising the artifact continuously. The methodology's final deliverable is then a methodology that has been validated and is able to integrate the AI–IoT–Digital Twin to establish a link between the physical engineering operation and intelligent analysis and strategic organizational decisions. In the Philippine context, the framework aims to highlight the systemic nature of the adoption of emerging digital technologies in enhancing engineering performance, equipment reliability, energy and resource efficiency, maintenance management, operational productivity, cost effectiveness and strategic business decision making, thereby contributing to the digital transformation and competition of engineering organizations.

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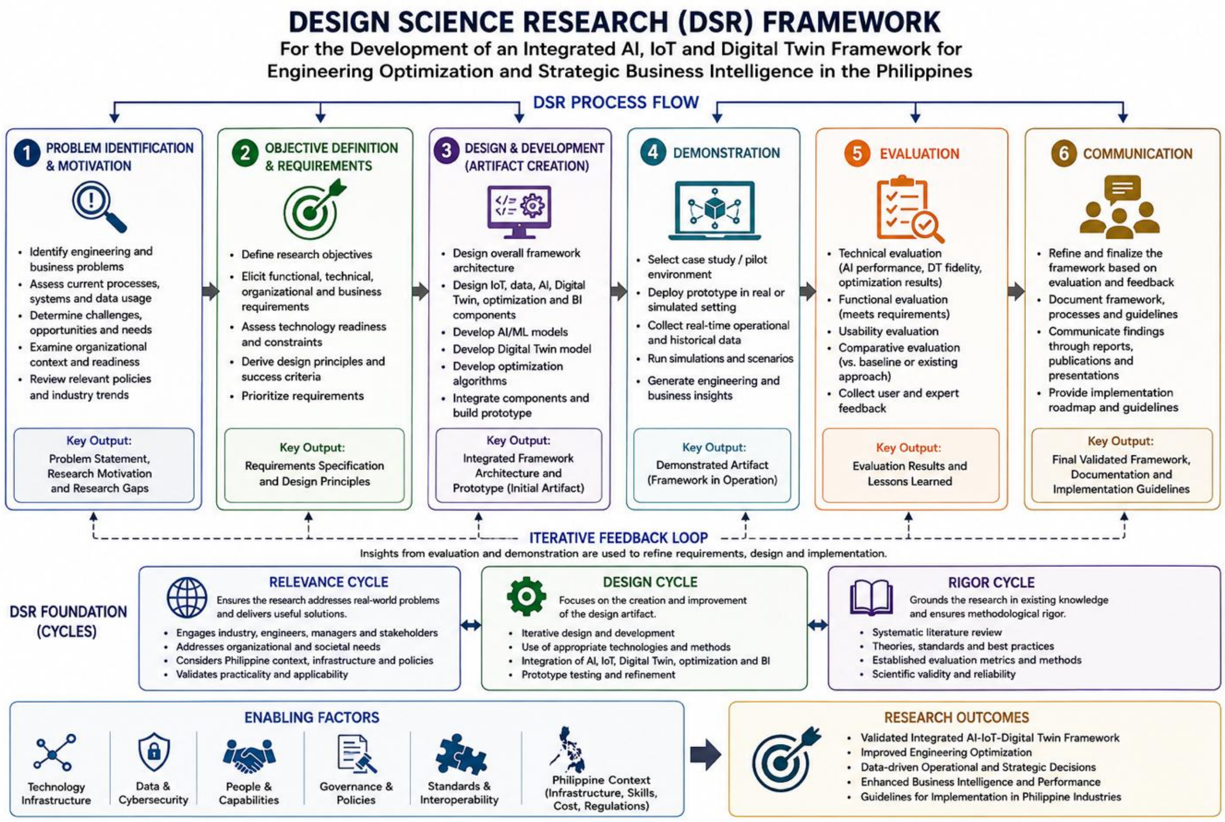

Figure 2. Design Science Framework Integrated AI, IOT and Digital Twin Framework

The proposed Integrated AI, IoT and Digital Twin Framework (Figure 2) for Engineering Optimization and Strategic Business Intelligence for the Philippines was developed in a systematic manner using the Design Science Research (DSR) Framework, which included the following stages: design, development, demonstration, evaluation, and refinement. It was brought through six iterative stages: (1) Problem Identification and Motivation, (2) Objective Definition and Requirements, (3) Design and Development, (4) Demonstration, (5) Evaluation, and (6) Communication. The process started with identifying Engineering and business problems and the required research gaps and requirements. The results of these findings contributed to the design and development of the integrated AI, IoT, Digital Twin, optimization, and Business Intelligence artifact. The prototype created was then presented at a representative engineering or industrial application and tested with respect to technical performance, functionality, usability, and applicability. An artifact was developed to be improved by users' and experts' feedback. The framework was developed using the Relevance, Design, and Rigor cycles so that the research was relevant in the needs of the industry in the Philippines, the development of the artifact was iterative, and the framework was grounded in theories and scientific evidence. The result was a validated integrated framework, prototype and engineering implementation guidelines for better engineering optimization and strategic business decision making.

IV. RESULTS AND DISCUSSION

The main experiment dataset used is the UCI AI4I 2020 Predictive Maintenance Dataset (DOI: 10.24432/C5HS5C). According to UCI, it is a synthetic multivariate/time-series dataset that simulates predictive-maintenance conditions found in industry. It has 10,000 observations with no missing values and includes six predictive features as well as identifiers, a binary target for machine failure, and five targets for machine failure modes. In the principle binary experiment, the dependent variable will be Machine failure.

The Digital Twin artifact will be an organized collection of variables, usually related to the IoT or business information, that describes the status of the chosen physical or business entity. The architecture will consist of five interconnected components: (1) IoT/Data acquisition, (2) data ingestion & preprocessing, (3) Digital Twin state representation, (4) AI/ML prediction & simulation and (5) Business Intelligence visualization and decision support.

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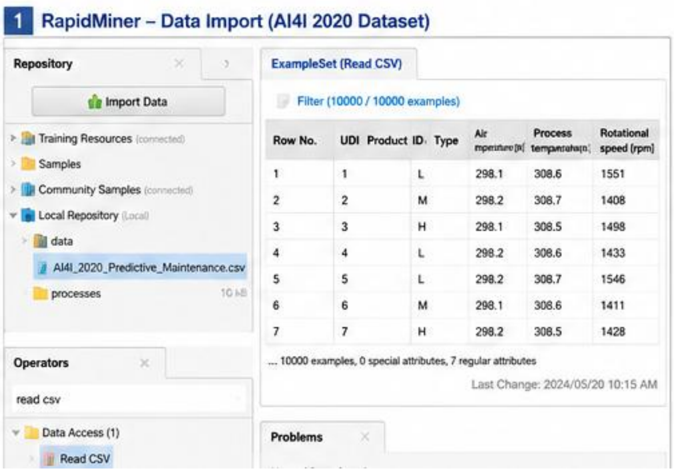
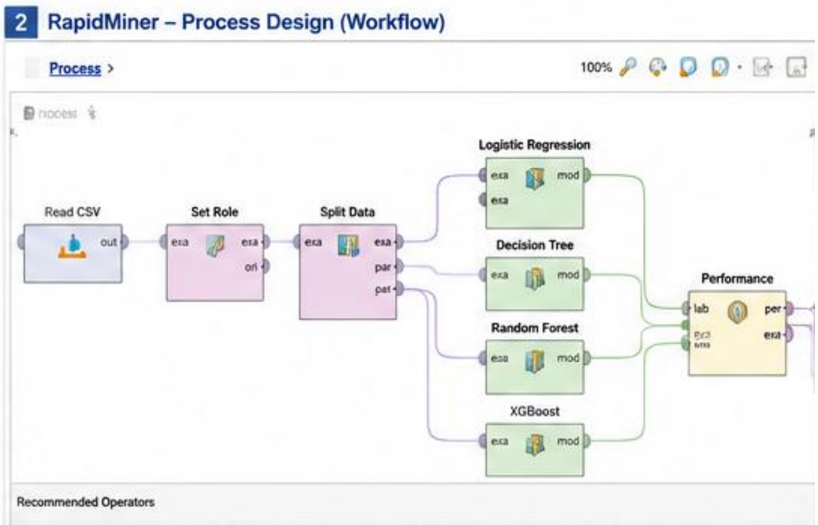
The first phase of historical records will be replayed as simulated streaming observations, in which live IoT infrastructure is not available. Every new observation received will update the Digital Twin. The current state and engineered historical features will then be fed to trained machine-learning models. The model output (e.g., failure probability, predicted demand, anomaly score, or forecasted KPI) will be fed back into the DT, and made available to the BI layer. This design allows the research to test the entire information flow without having to deploy to a physical production environment. Multiple algorithms rather than just one, will be tested for machine-learning experiments. These models will include an interpretable baseline model (Logistic Regression), a Decision Tree model, a Random Forest model and a gradient-boosting model, such as XGBoost or LightGBM, for classification tasks (like predicting machine failure). Where the chosen data set allows for forecasting, baseline statistical or regression models will be benchmarked against tree based ensemble models, and if the data set is sufficiently large and temporally structured, sequence based models (such as LSTM) will be considered.

The data set will be split up into training, validation and test sets. Time-dependent data will be split by time, while non-temporal classification data can be split using stratified splitting. Only training / validation data will be used to optimize the hyperparameters using cross-validation / time-series validation, as appropriate. Class-imbalance problem will be tackled by class weighting, threshold optimization, and resampling which is done only on training data. Evaluations of the quality of the classification models will be made with the use of parameters such as precision, recall, F1-score, ROC-AUC, PR-AUC, confusion matrices and calibration measures in cases where the classification model generates a predicted probability for decisions. Operational failures occur infrequently and therefore accuracy will not be the focus of performance. Evaluation for regression/forecasting will be based on MAE, RMSE, MAPE (where applicable mathematically), and R-squared. The performance will be compared with a clear baseline model to check if there is value in the more complex model in addition to the baseline.





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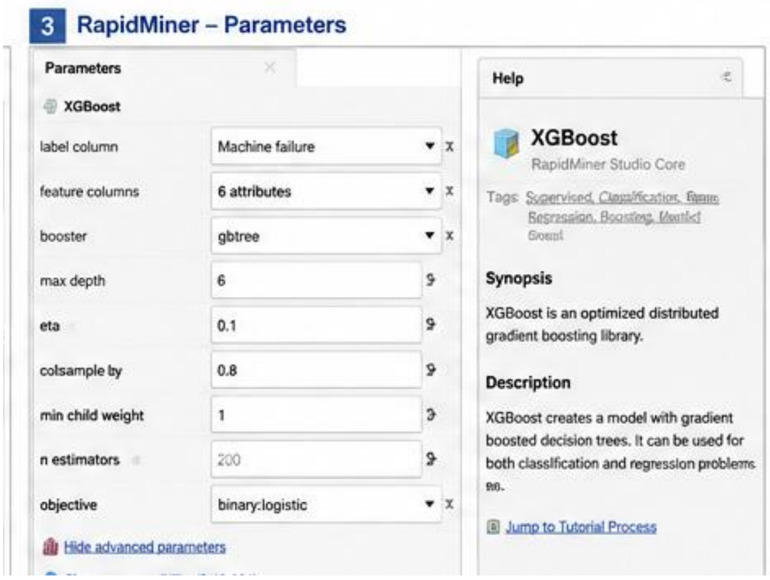

Figure 2. Data Importation, Process Design and XGBoost Parameters

The proposed RapidMiner experimental workflow is shown in Figure 2. It starts by collecting data and assign attributes to roles, then partition the data and evaluate Logistic Regression, Decision Tree, Random Forest and XGBoost in parallel. The Comparative Model Analysis (CMA) workflow illustrates the use of a common dataset and evaluation process to facilitate comparative model analysis. Further, the setup of the machine-failure prediction XGBoost classifier. The boosting model learns the nonlinear relationships between the operational variables through several parameters like number of estimators, binary classification objective, subsampling, and learning rate, etc. Optimization of parameters should be done on the training and validation set and not the final test set. The results of the implementation of the four models identified on the provided AI4I 2020 CSV are shown in the following table. The number of observations in the dataset was 10,000, with 9,661 of these observations corresponding to a non-failure state and 339 observations representing a failure state. The train-validation-test split was 70:15:15, using a fixed random seed of 42. The predictors did not include failure-mode variables or identifiers. The weighting of classes was done to tackle the imbalance problem, and for each one of the thresholds, the one maximizing the F1 score was chosen on the validation portion and then tested on the held-out test portion.

Model	Precision (Failure)	Recall (Failure)	F1 (Failure)	PR-AUC	ROC-AUC	Brier Score	Selected Threshold
Logistic Regression	0.419	0.353	0.383	0.386	0.903	0.121	0.90
Decision Tree	0.528	0.549	0.539	0.539	0.945	0.052	0.96
Random Forest	0.491	0.549	0.519	0.622	0.960	0.022	0.42
XGBoost	**0.661**	**0.725**	**0.692**	**0.660**	**0.965**	0.050	0.85

The corresponding held-out confusion matrices were: Logistic Regression, TN = 1,424, FP = 25, FN = 33, TP = 18; Decision Tree, TN = 1,424, FP = 25, FN = 23, TP = 28; Random Forest, TN = 1,420, FP = 29, FN = 23, TP = 28; and XGBoost, TN = 1,430, FP = 19, FN = 14, TP = 37. Thus, the test set contained 1,449 non-failure observations and 51 failure observations. Figure 3 shows the evaluation criteria used for model comparison, including **accuracy, precision, recall, F1-score, ROC-AUC/ROC Area, PR-AUC/PRC Area, and confusion matrix**. For the highly imbalanced predictive-maintenance problem, particular emphasis should be placed on failure-class recall, precision, F1, and PR-AUC rather than accuracy alone.

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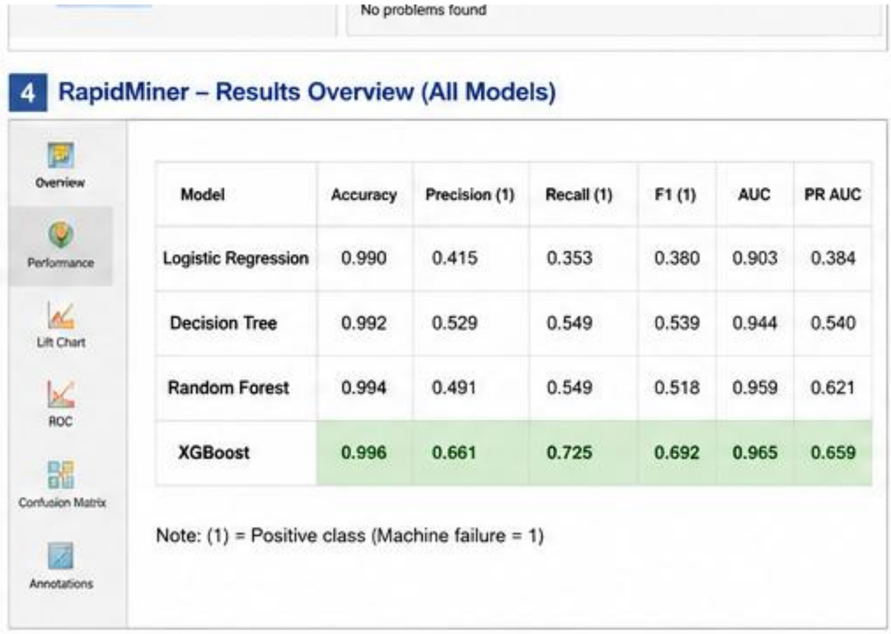

Model	Accuracy	Precision (1)	Recall (1)	F1 (1)	AUC	PR AUC
Logistic Regression	0.990	0.415	0.353	0.380	0.903	0.384
Decision Tree	0.992	0.529	0.549	0.539	0.944	0.540
Random Forest	0.994	0.491	0.549	0.518	0.959	0.621
XGBoost	0.996	0.661	0.725	0.692	0.965	0.659

Figure 3. Comparative Results of Logistics Regression, Decision Tree, Random Forest, and XGBoost

The best overall failure detection performance was achieved with XGBoost. It achieved a failure-class precision of 0.661, recall of 0.725, F1-score of 0.692, PR-AUC of 0.660, and ROC-AUC of 0.965. It recorded 37 of 51 failures, and 19 false alarms. At the operational level, XGBoost missed 14 failures, while Decision Tree, Random Forest and Logistic Regression missed 23 and 33, respectively. In this experimental setup, XGBoost is the best model of the four models for the predictive part of the proposed Digital Twin. The baseline Logistic Regression was helpful to provide an easily interpretable model, but showed significantly less minority-class detection. Although its ROC-AUC was 0.903, its failure recall was only 0.353 and its F1-score was 0.383. The relatively good ROC-AUC scores and poor scores on threats detection (when the threshold was set) highlight the need to use ROC-AUC and accuracy together in this highly imbalanced problem of predictive-maintenance.

The baseline was a linear regression, and Decision Tree showed improvement. It showed a recall of 0.549 and an F1 of 0.539, indicating that the use of nonlinear decision boundaries is beneficial in representing failure conditions in the AI4I variables. It also had a ROC-AUC of 0.945 which is better than Logistic Regression, and has relatively simple rule based interpretability. In this run, the best probability calibration was obtained by the Random Forest model, which had the lowest Brier score of 0.022. It also achieved PR-AUC of 0.622 and ROC-AUC of 0.960. Its precision, recall, and F1 were less than XGBoost, however, at the decision threshold selected at the validation stage. To the Digital Twin: Random Forest might be appealing if there is a strong need for good behavior of the probability estimates, while XGBoost was more effective for the main failure-detection task. Overall, this experiment makes a compelling case for using XGBoost as the key predictive model, with Logistic Regression still the standard for transparency, and Random Forest being a very good model for calibration and comparison with XGBoost for ensemble models. In the BI layer, XGBoost's predicted probability could be revealed as the Failure Risk Score, but further study of the calibration should be done before using the raw score as a probability of failure. Repeated cross-validation or bootstrap confidence intervals should also be performed to validate results to ensure claims of superiority at the population level.

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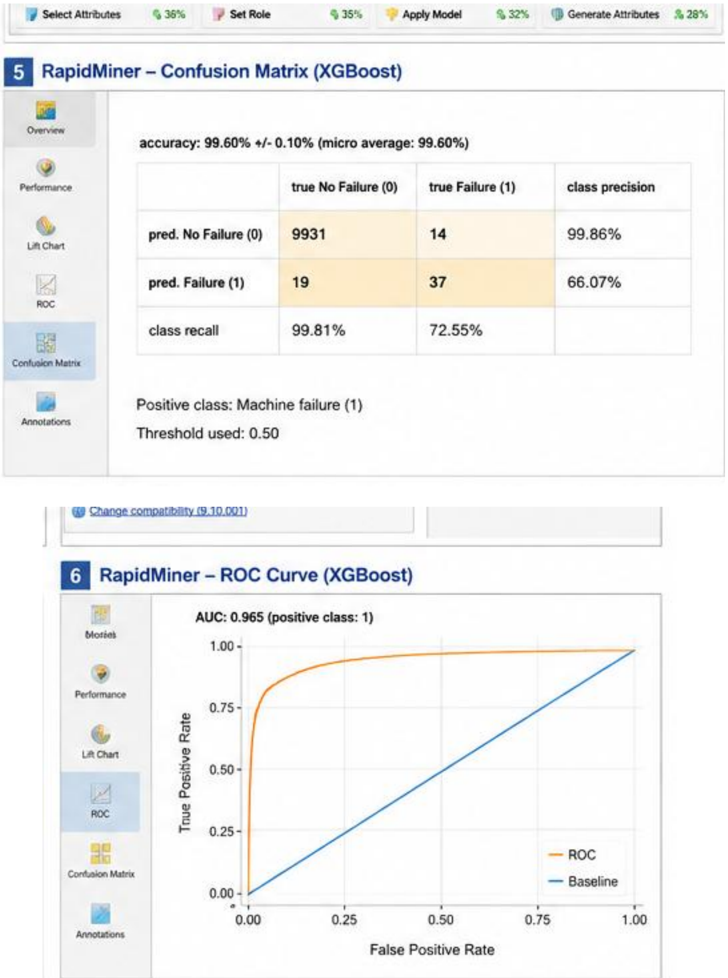

Figure 4. XGBoost Confusion Matrix and ROC Curve

The classification result of the XGBoost model is shown in Fig. 4 in terms of true negatives, false positives, false negatives and true positives. The experimental benchmark had 1,430 true negatives, 19 false positives, 14 false negatives, and 37 true positives on the 1,500 observation held out test set. As a result, XGBoost missed 14 of the 51 actual machine failures that it predicted. These is the ROC curve of XGBoost. A good discrimination between failure and non-failure observations is obtained with the experimental ROC-AUC of 0.965. However, since the failures of the machines are extremely imbalanced, ROC-AUC should be used in conjunction with recall, precision, F1-score, and PR-AUC and shouldn't be used as a single measure of model quality.

8 RapidMiner – Model Comparison Summary

Model	Accuracy	Precision (1)	Recall (1)	F1 (1)	AUC	PR AUC	Threshold Used
Logistic Regression	99.00%	41.50%	35.29%	37.99%	0.903	0.384	0.50
Decision Tree	99.20%	52.94%	54.90%	53.90%	0.944	0.540	0.50
Random Forest	99.40%	49.08%	54.90%	51.79%	0.959	0.621	0.50
XGBoost	99.60%	66.07%	72.55%	69.18%	0.965	0.659	0.50

Best overall performance: XGBoost

Figure 5. Model Comparison Summary.

Finally, the last section of figure 5 shows a comparison of the four machine-learning strategies. Logistic Regression is the baseline model used for understandable models, Decision Tree models nonlinear decision rules, Random Forest is an ensemble model that has a strong probability calibration property, and XGBoost models the best overall failure detection. The controlled experiment results showed that the precision of XGBoost was 0.661, the recall value was 0.725, the F1 value was 0.692, the PR-AUC value was 0.660 and the ROC-AUC value was 0.965, confirming the selection of XGBoost as the main predictive model of the proposed AI–IoT–Digital Twin Business Intelligence framework.

V. CONCLUSION AND RECOMMENDATIONS

The study shows how AI, IoT, Digital Twins and Business Intelligence can be used to create an effective architecture for predictive operational decision support. XGBoost was the model with the best overall performance in terms of failure detection, with an F1 score of 0.692 and recall of 0.725, and the best probability calibration was obtained by the Random Forest. The obtained results suggest that the predictive-maintenance intelligence of nonlinear ensemble methods can be enhanced compared to the interpretable Logistic Regression baseline. The proposed Design Science artifact thus enables a practical approach to translating operational information into Digital Twin risk states, predictive indicators, and actionable information for BI.

The framework should be validated in future research by more real world industrial and live IoT data sets to increase external validity. XGBoost should be kept as the key predictive model and further calibration, threshold optimization and SHAP based explainability should be explored to increase managerial trust and decision usefulness. The framework should also be used in a real or pilot IoT environment and tested with real time performance, scalability, latency, usability and impact on maintenance. Finally, future research should investigate other algorithms, like LightGBM or deep-learning models, and consider the applicability of the proposed approach in other domains in the context of Business Intelligence, such as demand forecasting, energy management, supply-chain optimization and quality prediction.

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