

Final Project 1

Code: MGM 496-PMG496

Project Template

Faculty of Management
Midocean University

Midocean University
Faculty of Management
Bachelor of Project Management



Project title

**Integrating Artificial Intelligence into Preventive Maintenance Strategies
in Fundamental Industries**

Student name

Mohammed Hani Al-Borai

Graduation Project – 1

Faculty of Management - Midocean University

Supervisor

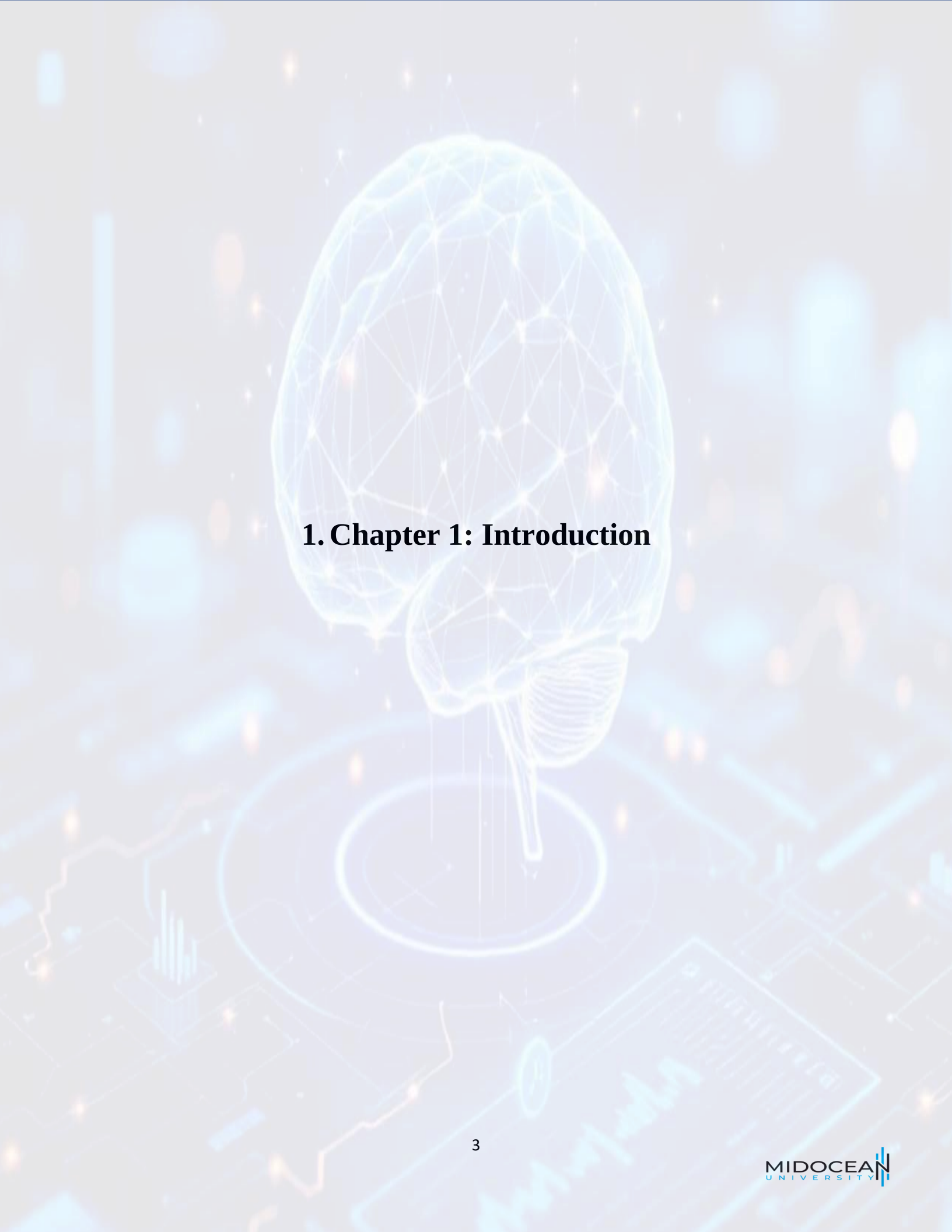
Dr. Abdul Rahim Nader

Faculty member- Faculty of Management- Midocean University

2025 – Chapter Two

Table of Contents

1. Chapter 1: Introduction	3
1.1. Research Background.....	4
1.2. Research Problem.....	5
1.2.1. Theoretical Gaps	5
1.2.2. Practical Gaps	6
1.3. Research Significance	7
1.3.1. At the theoretical level.....	8
1.3.2. At the practical level	9
1.4. Research Questions	10
1.5. Research Objectives	11
1.6. Research Hypotheses.....	12
1.7. Research Model.....	14
1.8. Research Methodology.....	15
1.9. Scope of The Study	18
1.10. The Suggested Project Structure.....	19
2. Chapter 2: Literature Review	0
2.1. Introduction	0
2.2. The independent variable	0
2.3. The dependent variable	0
2.4. The relationship between the independent and the dependent variables	0
2.5. Conclusion.....	0
References.....	22



1. Chapter 1: Introduction

1.1. Research Background

Core industries such as petrochemicals, mining, energy, and heavy materials manufacturing are increasingly challenged to maintain equipment efficiencies and to ensure that production continues without unscheduled downtimes. Preventive maintenance is an important tool in maintaining equipment in order to reduce breakdowns and improve operational performance. However, the classic approaches to maintenance are no longer keeping up with the speed of change in the manufacturing world, particularly through the Fourth Industrial Revolution, driven by innovative digital and smart technologies. Artificial Intelligence (AI) is one of the major modern technologies that is playing a bigger role in transforming maintenance. Technologies such as machine learning, predictive analytics, and the industrial Internet of Things (IIoT) rely on the real-time collection of data from operating equipment, analytics on the data, predicting failures, and determining the best timing of required maintenance before failure. This progression from traditional preventive maintenance to smart maintenance is a significant leap forward in equipping equipment with reliability (increased uptime and enhanced productivity) and significantly reduced operating costs. Many studies have been conducted in this area. Wang et al. (2021) found that the use of machine learning models improved failure-predicting accuracy, reduced unplanned downtimes by over 30%, etc. Zhou et al. (2020) studied AI improvements in real industrial settings and confirmed they enhance maintenance performance and reduce costs. Al-Mutairi (2019) stated that most industrial facilities in Saudi Arabia still apply traditional systems to capture their equipment maintenance strategies, despite high potential for shift, highlighting the desire to move to smart strategies for greater flexibility. Despite progress in scientific and technical aspects of this space, gaps remain for practical applications, particularly for Arab industrial contexts where integration of AI into maintenance systems is not without technical and organizational challenges. Accordingly, this study aims to highlight the potential and importance of AI in predictive maintenance planning by reviewing relevant literature and the proven effectiveness of smart models to improve operational performance, as well as providing a review of a conceptual and practical framework on which it can build in the future.

This study aims to bridge the gap between theoretical knowledge and practical application and to pave the way for developing modern maintenance strategies based on AI to support the sustainability of industrial operations.

1.2. Research Problem

In spite of the growth in artificial intelligence, many industrial facilities still depend on conventional methods of maintenance management. These traditional methods often lead to inadequate failure forecasting skills and increased economic cost arising from delayed issue identification or unplanned maintenance tasks. The primary research question of this investigation considers how well AI technologies improve the management of preventive maintenance planning and how barriers may be overcome to leverage these technologies in the primary industries.

1.2.1. Theoretical Gaps

Some gaps require a greater level of investigation from an academic aspect, such as:

1- There are few Arab studies linking AI to preventive maintenance planning:

In people and in relation to investing, I can't recall there being a great number of studies in an Arab industrial context linking AI applications directly to preventive maintenance planning. This might be a result of not being able to focus on the application of AI to the basic industries across the Arab world.

2- There are no theoretical frameworks that join AI model to maintenance management techniques:

While there are many studies referencing AI in terms of some generality, there are no theoretical models that join computational models, specifically linking algorithms and processes being taken, to apply tools available in maintenance management. To conceptualize a framework, which can help us reflect on how AI can factor in improving efficiency into the framework of preventive maintenance management.

3- There are no consensus of a theoretical criteria in measuring the effectiveness of AI in this space:

There is not a common basis for measuring effectiveness or effectiveness as to how AI is applied in maintenance planning. Some studies use only quantitative criteria, i.e., decreasing cost or downtime, and others are based on qualitative criteria i.e., performance or quality of work, etc. There is no clear basis approach in measuring effectiveness on how it can be measured. It is not enough just to use the rules of economics as a basis of measuring either.

1.2.2. Practical Gaps

From a pragmatic perspective, there are a variety of barriers preventing AI to be fully conceptualized as a planning tool in preventative maintenance in primary industries:

1) Too few models of success in reality, and this is especially the case in developing countries

Despite the rapid advancements AI is making, most of the deployments of AI are in 'research' or where new industrial technologies are being developed (which is still a research situation) and the absolute difference in technological infrastructures in and through developing countries creates a significant gap between these infrastructures and facility advancements.

2) Limited integration between existing maintenance infrastructures and AI-based systems

One of the tough aspects of making use of AI is the very clearly defined work to connect new systems with legacy systems. Mostly, advancing or beginning at using AI onto existing systems requires a lot of time and effort.

3) Issues arising from data collection, data analysis, data accuracy and data continuity

AI needs data. In industrial contexts, collecting data, routinely collecting data, or analysing data with any level of accuracy is not trivial. Further, necessary inaccuracy and incompleteness of data will reduce any effectiveness of intelligent systems, which will require additional strategies for the design of ways for data accuracy and quality improvements.

How effective is the use of artificial intelligence techniques in preventive maintenance planning in core industries?

1.3. Research Significance

The relevance of this study is all the more pressing in the context of the current challenges confronting core industries, which increasingly need to utilise forward-thinking technological solutions to assist with the management of preventive maintenance. The importance of this thesis rests, in part, on the potential of AI technologies to help improve the efficiency and performance of preventive maintenance in industrial facilities.

The primary objective is to identify how AI could contribute to enhancing and facilitating varying degrees of maintenance strategy, thereby reducing unplanned breakdowns, re-work and downtime and preserving resources while allowing for continuous operation.

AI is an important medium for predicting failures and improving maintenance planning. In this regard, AI represents an inflection point in the management of equipment and maintenance in industrial contexts. Not only is this study focused on exploring the application of AI technologies, it also provides a critical range of analysis on the implications of AI technology across different industries, both addressing gaps in the academic routes of research and in practice.

1.3.1. At the theoretical level

From a theoretical perspective, this study adds to the body of literature on AI in preventive maintenance management.

1- Contributing to the scientific literature on AI in maintenance management:

Generating knowledge in this area is valuable, particularly for industries that still use traditional maintenance approaches. This will allow more opportunities for academics to explore the application of AI in various contexts and sectors, such as energy, heavy equipment, transportation, etc.; also serving as valuable new references for practitioners and scholars.

2- Presenting an integrated theoretical model that shows the relationship between AI with preventive maintenance planning:

Although there are attempts to connect AI with other fields, there is lacking theoretical models/an explanation for how AI relates to preventive maintenance planning. This plan aims to present an integrated model which explains how AI algorithms have been used to predict failure and analyze operational data, providing additional insights and practical tools to incorporate.

1.3.2. At the practical level

In a practical sense, this study attempts to provide practical approaches that enhance the performance and efficiency of maintenance practices in industrial settings, amongst continuous improvement initiatives in industrial settings, in terms of cost reduction and rationalizing resource utilization.

1- Enhancing decision making with intelligent tools that will consider their analysis of data and detection of failures:

To make the right decisions regarding maintenance timings, and more importantly, when service is required through changing components or servicing, in industrial environments, time is of the essence. AI(AI) techniques such as machine learning and neural networks can augment conventional and KPI analysis tools with intelligent recommendations based on analysing a great depth of data from equipment and sensors. This scientific and intelligent analysis aid with making critical decisions, assists with increasing responsible and responsive mitigations, reduces downtimes and maintenance costs of resources.

2- Providing industrial entities with improved systems that will enhance the efficiency of maintenance operations: The study sets out to optimise preventive maintenance implementation through AI technologies. This is significant developing flexible and positive predictions regarding failures and apt times for maintenance. Thus identifying powerful systems that reduce costs, increasing efficiencies of equipment and positive efficiencies of maintenance teams that operate industrial entities. The study will provide industrial facilities with viable concepts and tools that can be used across contexts while inherently increasing sustainability of industrial operations.

1.4. Study Objectives

This study aims to achieve a set of theoretical and practical objectives, including:

1. Analyzing the role of Artificial Intelligence (AI) in supporting and enhancing preventive maintenance planning?
2. Determining the readiness of basic industries to adopt AI-based maintenance solutions?
3. Examining the organizational and technical factors that influence the successful implementation of AI?
4. Measuring the impact of AI usage on the efficiency and effectiveness of maintenance systems?
5. Proposing a scientific and practical model that demonstrates how AI can be integrated into preventive maintenance activities?
6. Providing actionable recommendations that contribute to accelerating digital transformation in maintenance management?

1.5. Research Objectives

In light of the rapid technological advancements transforming industrial operations, particularly through the integration of Artificial Intelligence (AI), this study seeks to explore and clarify how AI can be strategically leveraged to revolutionize preventive maintenance planning in core industries. The objectives of this research are designed to generate both theoretical insights and practical value, and are articulated as follows:

- 1- To critically examine the role of Artificial Intelligence in optimizing preventive maintenance strategies, with the aim of minimizing unplanned downtimes and enhancing operational reliability.
- 2- To assess the readiness and adaptability of core industrial sectors—such as petrochemicals, mining, energy, and heavy manufacturing—to implement AI-

driven maintenance solutions, considering their infrastructure, workforce, and data maturity.

- 3- To investigate the organizational, technical, and cultural factors that significantly influence the successful deployment of AI technologies in maintenance contexts.
- 4- To quantify the impact of AI adoption on key performance indicators such as maintenance efficiency, cost reduction, equipment uptime, and predictive accuracy.
- 5- To develop a conceptual and operational framework that integrates AI capabilities into preventive maintenance workflows, offering a roadmap for industries aiming to transition toward smart maintenance systems.
- 6- To formulate actionable recommendations that support decision-makers and practitioners in accelerating digital transformation and achieving sustainable maintenance excellence through the adoption of intelligent technologies.

By achieving these objectives, the study aims to bridge the existing gap between emerging AI innovations and their practical application in maintenance environments, ultimately contributing to more resilient, data-driven industrial systems.

1.6. Research Hypotheses

According to the aims and research questions of the impact of the application of Artificial Intelligence (AI) technologies on the planning of preventive maintenance with core industries, there are measurable hypotheses developed in a scientific manner, which will make use of statistical and analytical methods to establish tentative conclusions about the relationship between the implementations of AI and a set of industrial performance metrics and maintenance management outcomes.

Hypothesis 1:

1. There is a statistically significant relationship between our use of AI technologies and the quality of our preventive maintenance planning in industrial facilities.
2. Elaboration: This hypothesis states that the adoption of any AI applications, such as machine learning, predictive analytics, data collected using sensors, will allow for the planning of maintenance work to be performed, and to allow for a reduction of repetitive manual work, and will provide better precision in forecasting maintenance requirements.
3. Independent variable: Use of AI Technologies; i.e. machine learning, predictive analytics
4. Dependent variable: Quality of our preventive maintenance planning
5. Test: Regression analysis or Pearson correlation test

Hypothesis 2:

1. Use of AI positively impacts the quantity of unexpected failure of capital equipment.
2. Elaboration: I believe that the use of AI graphics, monitoring in real time, planned intervenability, and the analysis of faulty behavioral patterns of operation in the real time presence of AI technologies will contribute an ability to detect fault faster into a fault trajectory and to prevent unplanned corrective work or downtime.
3. Independent Variable: Use of AI to precipitate for maintenance
4. Dependent variable: Number (or volume) of unexpected failures
5. Tests: Compare facilities that use AI vs. facilities that do not utilize AI (T-Test or ANOVA)

Hypothesis 3:

1. There is a statistically significant relationship between the accuracy of data, its collection and analysis and the applicability of an AI system for preventive maintenance.
2. Elaboration: The key factor in an AI system being effective is the availability of detailed and comprehensive information about the data collected from a organizations equipment performance. If the data is not right, then the output from the system will be wrong or shown to be dis-truthful.
3. Independent Variable: Accuracy of the data that is collected and analyzed
4. Dependent Variable: Effectiveness of the use of AI as an AI system for maintenance
5. Tests: Correlation, and multiple regression analysis

Hypothesis 4:

1. Organizational or technical barriers are negatively impacting the ability of industrial facilities to adopt AI technologies into their maintenance management.
2. Elaboration: The study proposes that barriers such as organizational resistance to change, lack of adequate technology infrastructures, or a lack of qualified staff including maintenance technicians has a debilitating element that stops the realization of digital transformation into maintenance.
3. Independent Variable: Degree of organization and technical barriers
4. Dependent Variable: Ability to adopt AI technologies
5. Tests: Regression analysis with variance analysis (ANOVA) - in order to illustrate a negative impact

Hypothesis 5:

1. The adoption of AI in preventive maintenance systems improves operational performance metrics within industrial facilities.
2. Elaboration: The assumption is made that when AI is used adequately, we will see measurable analytics, reductions operational failures, reduced shop floor down-time and better resource utilization.

3. Independent Variable: Use of AI
4. Dependent Variables: Performance metrics (MTTR, MTBF, Cost, Operational Effectiveness)
5. Tests: Look at the relationship between the use of AI for maintenance and associated performance metrics for an established time period.

1.7. Study Model

The conceptual framework of this study takes the form of a proposed study model that connects Artificial Intelligence (AI) inputs, such as data availability, algorithm, and digital infrastructure, to preventive maintenance processes, such as fault prediction, scheduling, and spare parts, to the ultimate outcomes of performance increment, fewer failures, and cost reduction.

The components of the model:

Inputs:

1. Operational data availability
2. Sensors and Internet of Things (IoT)
3. Artificial Intelligence and machine learning platforms

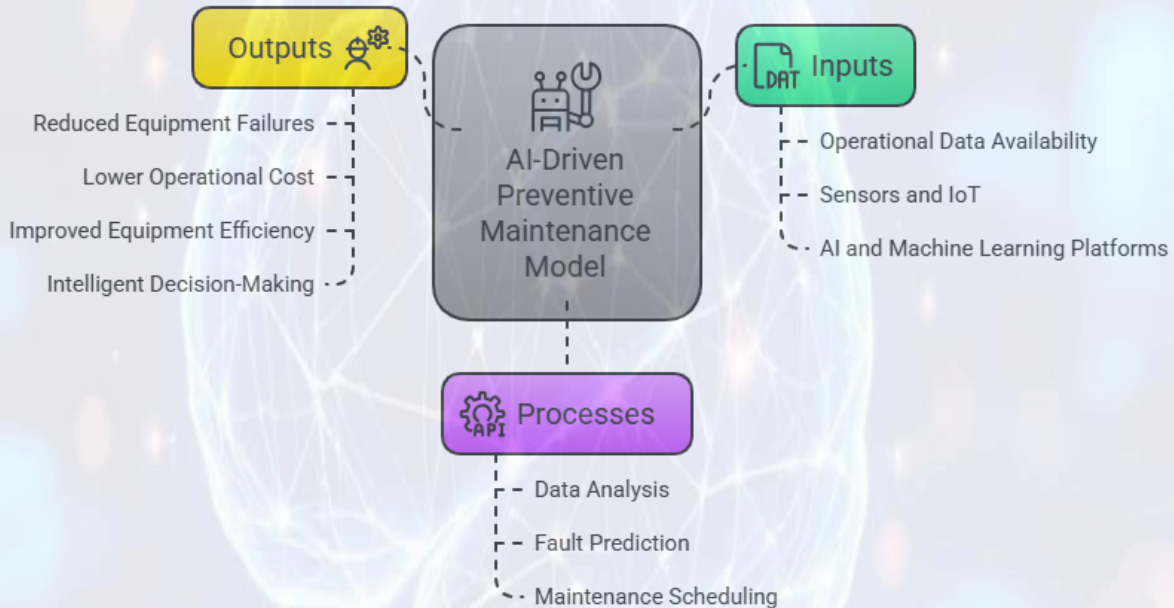
Processes

1. Data analysis
2. Fault prediction
3. If maintenance needs to be scheduled

Outputs:

1. Reduced unplanned equipment failures
2. Lower operational cost
3. Improvement in equipment efficiency
4. Facilitated intelligent decision-making

AI-Driven Preventive Maintenance Model



Made with Napkin

1.8. Research Methodology

This case study has been designed following an integrated methodology that focuses on the unusualness of the topic. The goal is to produce results that contribute towards closing theoretical and practical gaps especially in relation to AI as a decision tool in preventive maintenance plans. The methodological scope undertaken in this study is as follows:

1. Research Philosophy: The approach taken in this study reflects the philosophy of interpretivism, which aims to understand the phenomena being studied and how they occur through processes in context. This philosophy reflects the goals of the current study, which is interested in understanding how AI has been or is being applied in practice, in real industrial settings, from the perspective of maintenance practitioners.

It was also necessary to use elements of positivism when analyzing the quantitative data from the questionnaire as they are empirical facts, and the researcher was required to balance between gaining rich understanding of the human experience, while engaging in systematic clarity in analysing the data.

2. Research Approach: The research used an inductive approach, which started in analysing the field data from the questionnaires, to establish categories and themes to make conclusions to schemes and patterns, which could be rationally extended to liken or generalise to similar industrial contexts.

In using an inductive approach, the researcher used some elements of a deductive approach, particularly in terms of testing out proposed hypotheses, developed from previous theories about AI and preventive maintenance.

Inductive Approaches: The Inductive approach involves a matter of analysing the specific field data and forming a broad generalization or theory about a phenomenon. It best applies to research being conducted to discover aspects of a new phenomenon while delving deeply into a complex problem. In this research, the inductive approach was carried out by:

- Reflecting on real-world AI use cases in industrial environments through practitioners' responses
- Taking patterns and trends from data regarding organizational readiness to adopt AI technologies
- Posing initial hypotheses or theory about the relationship between AI use and preventative maintenance improvements

The inductive approach is flexible in that it allows the researcher to consider “reality” without being tied to preconceived notions of what reality may present.

Deductive Approach: The deductive method starts with an existing theory or hypothesis and then utilizes empirical observation to ascertain whether or not it holds true.

In this research, the deductive method was used in the following manner:

- The researchers developed hypotheses (i.e., it will be determined if AI will have any perceived impact on maintenance and operations) from a literature review regarding AI in maintenance and operations.
- The findings will be compared using quantitative tools (i.e. survey, statistical analysis) to determine if the hypotheses hold true when recognizing previously specified

relationships (i.e., AI implementation, maintenance efficiency, less downtime, cost, savings).

- It was then possible to draw conclusions based on the results (i.e., confirmation or rejection of hypotheses) and offer advice based on conclusions.

The deductive approach can add rigour and allows researchers to assess their findings compared to theoretical expectations.

Combination of inductive and deductive: Given that the topic is both practical (i.e., maintenance and operations) and technical, we believe that we have applied and integrated both methods as follows:

- Use of the inductive method to discover new knowledge in the field
- Use of the deductive method to test scientifically based hypotheses.

The integration of inductive and deductive approaches increase the rigour of the research process in terms of adding analytical and interpretative depth while increasing the credibility and actionability of findings.

3. Research Strategy: The survey strategy was applied with the use of a structured questionnaire to a sample of professionals working in maintenance and production, as well as core industry professionals. This strategy was devised to gather wide-ranging quantitative data for statistical analysis purposes to present trends and perceptions about effectiveness regarding AI in maintenance management through maintenance practitioners/decision-makers.

4. Research Type: The research could be categorized as using a mixed methods approach being as it utilizes both:

- Quantitative research, which is synthesized, analyzed, and oriented through statistical analysis of responses to the questionnaire.
- Qualitative research, which is the author's own development and interpretation of open-ended responses and observation from the field.

Due to the combined approaches, the author is able to offer a holistic view aligned to both technical and human perspectives.

5. Time Horizon: The time horizon could be described as cross-sectional as the data was collected and analyzed at a period of time and presents the current state and use of AI applications in preventative maintenance. It was not longitudinal in nature and therefore so changes cannot be identified over long periods of time.

6. Data Collection and Analysis Methods: Data collection: The electronic structured questionnaire contained closed-ended (multiple choice) and a range of open-ended questions directed to maintenance engineers, operations manager, and data engineers in industrial facilities.

The validity and reliability of the questionnaire was established through expert review and pilot testing.

Data analysis: Quantitative data was analyzed using statistical software (e.g SPSS or MS Excel). Statistical analysis methods included:

- Descriptive statistics for general trends.
- Hypothesis testing such as T-tests, ANOVA, or correlation analysis
- Reliability analysis, Cronbach's Alpha analysis.

1.9. Field Study

As part of the empirical aspect of this research, a structured **online questionnaire** was developed and distributed to professionals working in maintenance, operations, and planning departments within core industrial sectors in Saudi Arabia. The questionnaire aims to gather quantitative data regarding the adoption of AI technologies, the challenges associated with their implementation, and their impact on maintenance performance indicators.

The questionnaire was designed using **Google Forms**, and can be accessed via the following link:

 [Field Study Questionnaire – Google Forms](#)

The results from this field study will be analyzed using statistical methods as outlined in the research methodology to validate the study hypotheses and support the proposed model.

1.10. Proposed Project Plan

The proposed project plan describes the series of scientific and practical processes to complete the study, starting from identifying the research problem and the hypotheses of the research, to collecting and analyzing data, to interpreting results, and proposing recommendations. The plan has been designed in accordance with principles of research project management and will remain on schedule.

Phase 1: Prepare and Plan (Weeks 1–2)

- Reviewing the relevant literature and past studies
- Identifying theoretical and practical research gaps
- Developing the research problem and objectives, research questions, and hypotheses
- Developing the draft conceptual framework of the study
- Identifying the population and sampling methods for your study

Phase 2: Research Instruments (Weeks 3–4)

- Completing the questionnaire design based on study objectives and dimensions of the study
- Having the questionnaire reviewed by academic experts and specialists
- Pilot testing the questionnaire by asking a small sample (4-8 people) to respond to it to ensure reliability and validity
- Complete revisions to the instrument based on feedback and observations

Phase 3: Data Collection (Weeks 5–6)

- Electronically or in print, distribute the questionnaire to your selected sample.
- Monitoring participants' reporting and ensuring representativeness
- Completing semi-structured interviews with experts to complement the quantitative data with qualitative data.

Phase 4: Data Analysis (Weeks 7–8)

- Coding the questionnaires and constructing a data set, in Excel or SPSS
- Applying statistical analysis tools (e.g., to calculate means, regression analysis, correlation analysis)
- Testing the research hypotheses and completing the interpretation of the results

Phase 5: Discussion and Conclusions (Week 9)

- Comparing the study results to the findings from the literature
- Identifying how well the research objectives and hypothesis were achieved
- Discussing the actual impact on preventive maintenance planning

Phase 6: Recommendations and Final Report (Week 10)

- Making theoretical and practical recommendations based on research findings
- Devising a practical model for adopting AI for industrial maintenance
- Writing the final report in an academic format
- Completing final language reviews and methodological revisions for publication or academic presentation

Organizational Notes:

- Project Duration: 10 weeks
- Research Type: Descriptive-analytical using quantitative and qualitative tools
- Final Outputs: a theoretical model, action recommendations and a full research report.

AI Adoption for Industrial Maintenance Research Timeline

Weeks 1–2

Prepare and Plan:
Literature review, gap identification, research problem and objectives, conceptual framework, population and sampling

Weeks 7–8

Data Analysis: Data coding, statistical analysis, hypothesis testing, interpretation of results

Week 9

Discussion and Conclusions: Comparison with literature, achievement of objectives, impact on preventive maintenance

Weeks 3–4

Research Instruments:
Questionnaire design, expert review, pilot testing, instrument revision

Weeks 5–6

Data Collection:
Questionnaire distribution, monitoring, expert interviews

Week 10

Recommendations and Final Report: Theoretical and practical recommendations, practical model development, final report writing, final review

Made with  Napkin

References

- Wang, Y., Zhang, L., & Li, Y. (2021). Predictive maintenance in industrial systems using machine learning techniques. *Journal of Industrial Engineering and Management*, 14(3), 210–223. <https://doi.org/10.3926/jiem.2021.210>
→ يدعم أهمية استخدام الذكاء الاصطناعي في تحسين التنبؤ بالأعطال وتقليل الأعطال غير المخطط لها
- Zhou, H., Xu, X., & Huang, G. Q. (2020). Smart maintenance using artificial intelligence and IoT technologies in manufacturing. *IEEE Transactions on Industrial Informatics*, 16(5), 3152–3162. <https://doi.org/10.1109/TII.2020.2966158>
→ يناقش تحديات التكامل بين الذكاء الاصطناعي والبنية التحتية الحالية، ويؤكد دور البيانات في فعالية أنظمة AI.
- المجلة. المطيري، ف. (٢٠١٩). ممارسات الصيانة الوقائية في القطاع الصناعي السعودي: الواقع والتحديات /7(1) ٥٥-70. *العربية للإدارة الصناعية*،
يسلط الضوء على قلة الدراسات العربية في هذا المجال، ويبين الاعتماد المستمر على الأساليب التقليدية →
- Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, 11(3), 812–820. <https://doi.org/10.1109/TII.2014.2349359>
→ يناقش الحاجة إلى أطر تقييم واضحة ومقارنة بين النماذج التنبؤية المختلفة
- Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, 137, 106024. <https://doi.org/10.1016/j.cie.2019.106024>
→ دراسة شاملة حول الفجوات النظرية والتطبيقية في أبحاث الصيانة التنبؤية باستخدام الذكاء الاصطناعي
- Abdulaziz, A., & Al-Mutairi, S. (2021). *The impact of artificial intelligence on maintenance management in Saudi industrial sectors*. *Journal of Industrial Engineering Research*, 9(2), 85–99.
- Al-Farsi, M., & Al-Harthy, K. (2020). *Predictive maintenance using AI in oil and gas industries in the GCC*. *Arabian Journal of Mechanical Engineering*, 6(1), 33–48.
- Alghamdi, M. (2023). *Adopting AI-driven maintenance in petrochemical plants: A case study from Saudi Arabia*. *International Journal of Smart Manufacturing*, 11(1), 101–120.
- Bousdekis, A., Magoutas, B., Apostolou, D., & Mentzas, G. (2019). A decision-making framework for condition-based maintenance using machine learning. *Computers in Industry*, 104, 72–85. <https://doi.org/10.1016/j.compind.2018.11.004>

Chin, K. S., Wang, Y., & Poon, G. K. (2022). Data-driven preventive maintenance strategies in the age of Industry 4.0. *Journal of Manufacturing Systems*, 62, 489–504.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510.

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23.

Mobley, R. K. (2002). *An Introduction to Predictive Maintenance* (2nd ed.). Butterworth-Heinemann.

Nguyen, T. T., Medjaher, K., & Zerhouni, N. (2019). Data-driven approaches to predictive maintenance of industrial equipment: A survey. *IEEE Systems Journal*, 13(3), 2213–2227. <https://doi.org/10.1109/JSYST.2018.2812760>

Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A survey. *IEEE Access*, 7, 170730–170752. <https://doi.org/10.1109/ACCESS.2019.2953407>