



Final Project 2

PMG 497

Project Template

Midocean University
Faculty of Management
Bachelor of Project Management



Project title

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

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2025 – Chapter Three

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who generously shared their knowledge, expertise, and guidance throughout my studies.

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whether through scientific advice, providing references, technical support, or moral encouragement.

This research is the product of your collective efforts, and I dedicate my sincere thanks and gratitude to all of you.

Dedication

To the soul of my beloved mother,

may Allah have mercy on her and grant her the highest place in Paradise.

You were the source of love, kindness, and endless prayers that guided me through every stage of my life.

You taught me that success begins with patience, faith, and trust in Allah.

Every achievement I make today is a reflection of your love, your sacrifices, and your everlasting presence in my heart.

To my dear father,

may Allah bless you with long life, good health, and happiness.

You are my role model, my strength, and my constant source of wisdom and guidance.

Your encouragement and support have been the foundation of every step I've taken, and your presence is one of the greatest blessings in my life.

To my beloved wife,

my life partner and unwavering supporter,

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Your love and faith in me have made this achievement possible.

And to my dear brothers and sisters,

you are my strength and pride,

always surrounding me with love, motivation, and support.

I dedicate this humble work to you all with deep love and gratitude.

Abstract

Purpose:

This research aims to investigate the role of Artificial Intelligence (AI) in enhancing preventive maintenance planning within core industrial sectors such as petrochemicals, mining, energy, and heavy materials manufacturing. The study focuses on identifying how AI technologies can optimize maintenance schedules, reduce equipment failures, and improve operational reliability in the context of Saudi Arabia's industrial transformation and Vision 2030.

Methodology:

A mixed-method approach was adopted, combining quantitative data collected through a structured questionnaire distributed among maintenance and engineering professionals in major industrial plants, and qualitative insights obtained from expert interviews. The data were analyzed to evaluate the current level of AI adoption, organizational readiness, and the main challenges facing the integration of AI in maintenance planning.

Findings:

The results reveal that while awareness of AI's potential in maintenance is increasing, its practical application remains limited due to technical, financial, and organizational barriers. However, industries that have begun adopting AI-based predictive maintenance systems reported noticeable improvements in equipment reliability, cost efficiency, and decision-making accuracy. The study highlights the importance of developing a clear digital strategy and capacity-building initiatives to accelerate AI integration in industrial maintenance.

Originality & Implication:

This research contributes to the limited body of literature focusing on AI-driven maintenance planning in the Arab industrial context, particularly in Saudi Arabia. It provides a practical framework for integrating AI tools into preventive maintenance systems, supporting industrial digital transformation, and enhancing sustainable operational performance across key sectors.

Keywords:

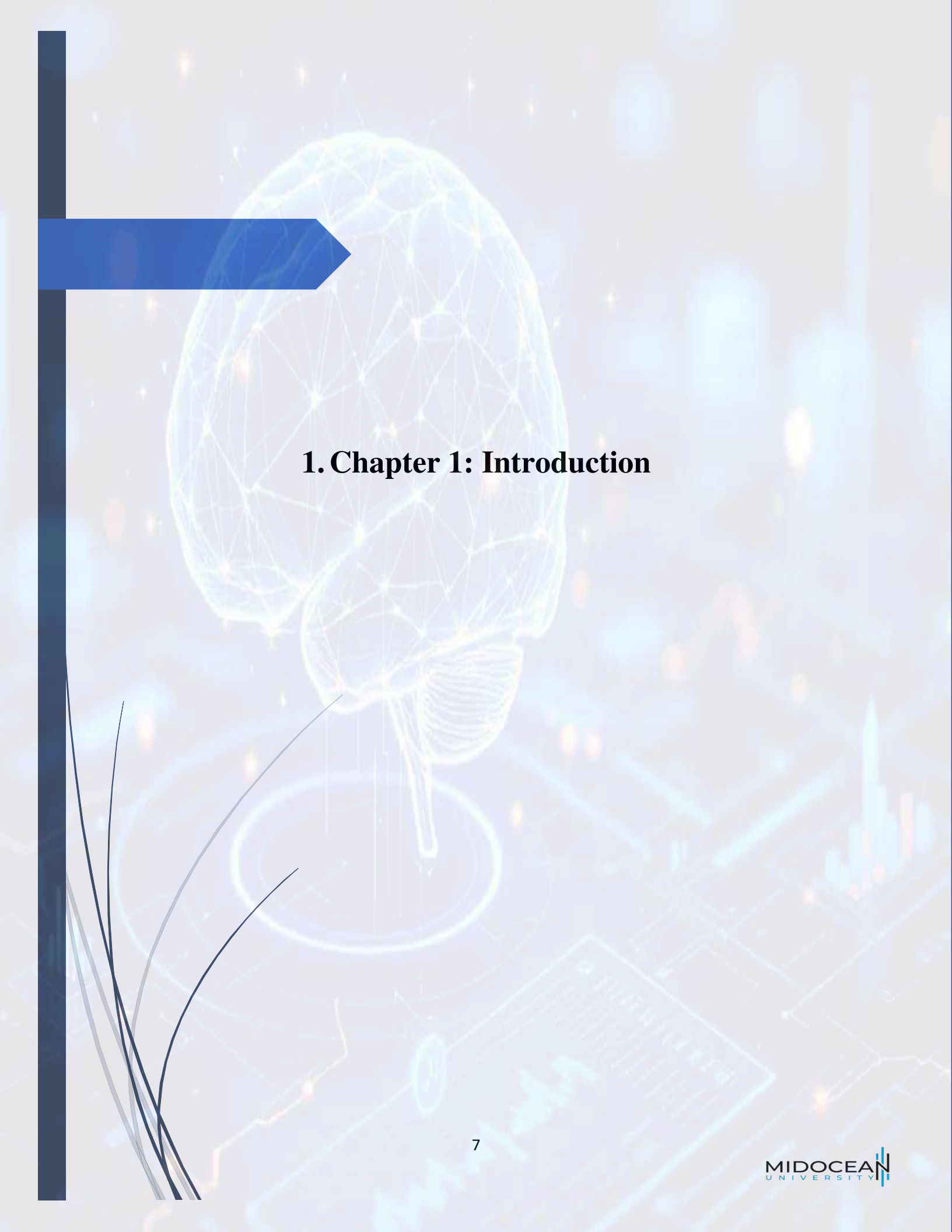
Artificial Intelligence, Preventive Maintenance, Predictive Analytics, Industrial Management, Digital Transformation, Saudi Arabia

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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

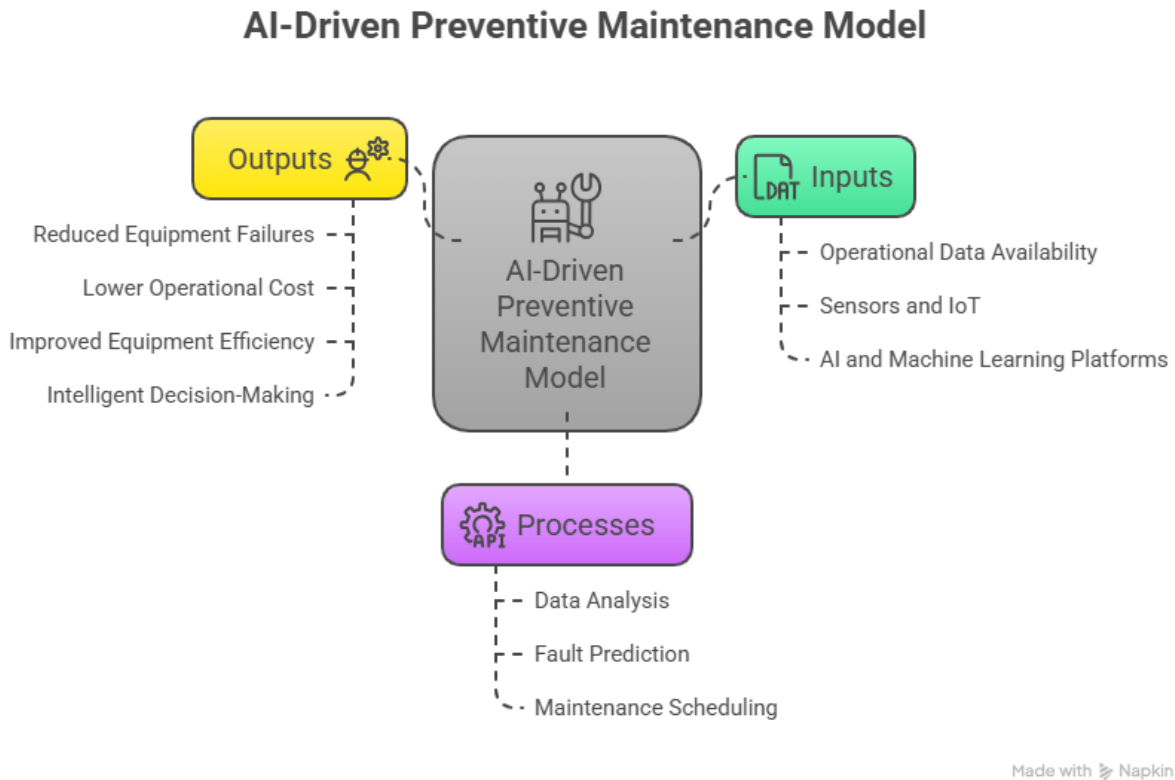


Figure 1: Study Model. Source: The Researcher. (2025)

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.

Research Methodology Pyramid



Figure 2: Research Methodology. Source: The Researcher. (2025)

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

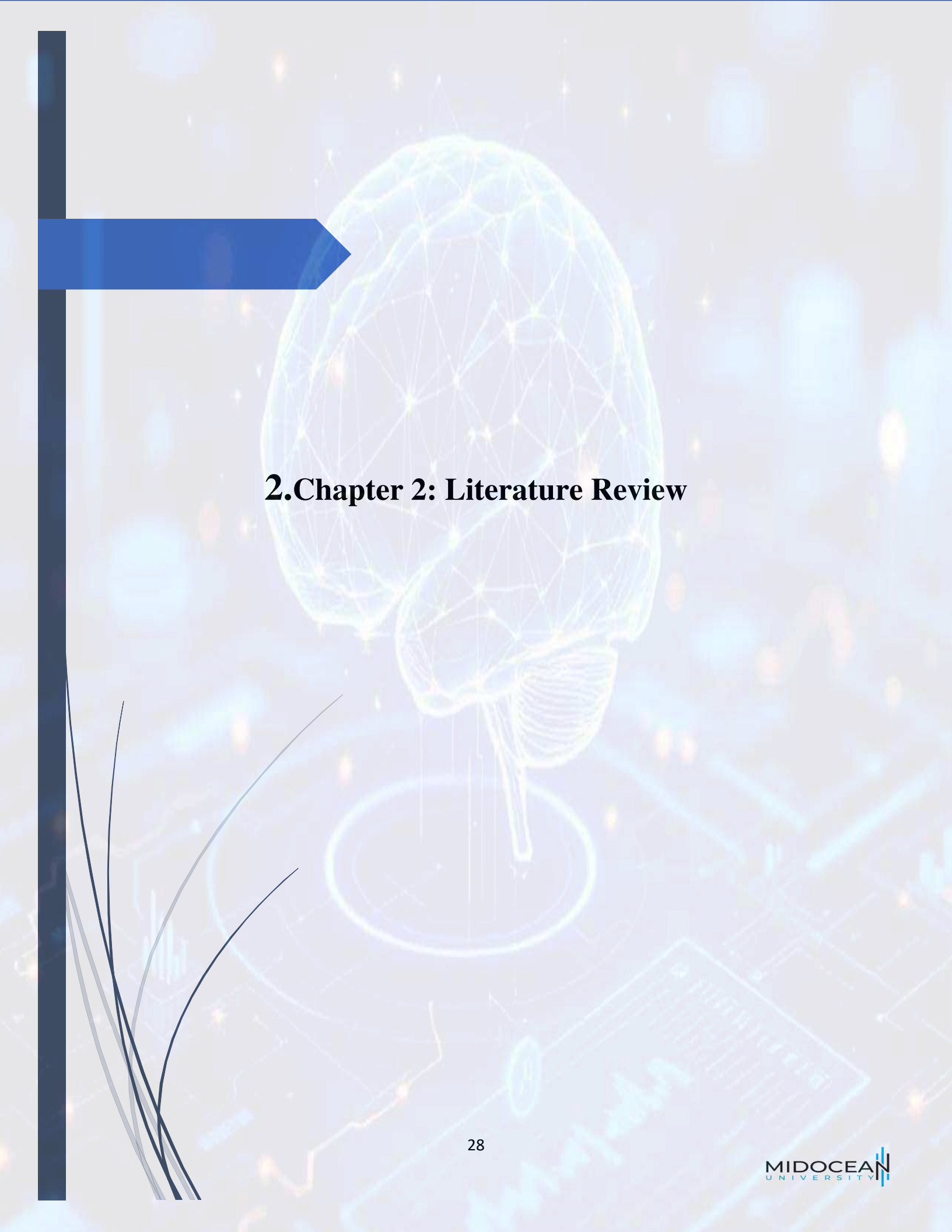
Organizational Notes:

- 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.

Project Completion Journey



Figure 3: Project Structure. Source: The Researcher. (2025)



2.Chapter 2: Literature Review

2.1. Introduction

In an era defined by rapid technological advancement and the ongoing Fourth Industrial Revolution, industries across the globe are facing increasing pressure to enhance productivity, reliability, and sustainability. Core industries—such as petrochemicals, mining, energy, and heavy materials manufacturing—are the backbone of national economies, especially in resource-driven countries like Saudi Arabia. These industries depend heavily on the availability and performance of complex machinery and equipment, where even minor failures can lead to costly downtimes, production losses, and safety risks.

Preventive maintenance has traditionally played a crucial role in maintaining operational continuity and minimizing unexpected equipment breakdowns. However, conventional maintenance methods, which rely on fixed schedules or reactive responses, are no longer sufficient in today's data-driven industrial environments. The emergence of Artificial Intelligence (AI), the Internet of Things (IoT), and predictive analytics offers new and transformative opportunities to redefine how maintenance is planned, executed, and optimized.

Artificial Intelligence, in particular, represents a paradigm shift from reactive or preventive strategies toward predictive and intelligent maintenance management. Through machine learning, pattern recognition, and real-time data analysis, AI systems can forecast failures before they occur, optimize maintenance schedules, and improve the overall reliability of assets. This transformation not only promises to reduce costs and downtime but also supports the broader goals of operational efficiency, sustainability, and digital transformation aligned with Saudi Vision 2030.

Despite the global progress in this area, a significant gap remains between theoretical knowledge and practical implementation, particularly in Arab industrial contexts. Many industrial facilities in the region continue to depend on traditional maintenance systems, facing challenges in data infrastructure, workforce readiness, and technology integration. Consequently, there is a growing need for empirical research that explores how AI can be effectively leveraged to enhance preventive maintenance planning in these industries.

This research seeks to fill that gap by examining the role of Artificial Intelligence in transforming maintenance management in Saudi Arabia's core industries. It aims to assess the readiness of industrial organizations to adopt AI-driven maintenance solutions, identify the barriers that hinder adoption, and propose a conceptual and practical framework that integrates AI technologies into preventive maintenance planning.

Ultimately, the study aspires to contribute both theoretically and practically to the field of industrial maintenance, offering insights that can help industries transition from traditional to smart maintenance systems, thereby achieving operational excellence and supporting national goals of industrial innovation and sustainability.

2.2. The Independent Variable: Artificial Intelligence (AI)

The independent variable in this study is **Artificial Intelligence (AI)**, representing the set of advanced computational techniques that enable machines to learn from data, recognize patterns, and make intelligent decisions with minimal human intervention. Within the industrial context, AI encompasses technologies such as **machine learning (ML)**, **deep learning (DL)**, **expert systems**, **neural networks**, and **predictive analytics**. These tools are increasingly applied to maintenance management to enhance operational efficiency and reliability.

AI-based maintenance systems utilize real-time data collected from sensors, Internet of Things (IoT) networks, and historical maintenance records to identify anomalies and predict potential equipment failures. This proactive approach shifts maintenance planning from a **time-based or reactive system** to a **condition-based and predictive system**, thereby reducing downtime, optimizing resource allocation, and extending asset life. In Saudi Arabia's industrial transformation journey under Vision 2030, AI represents a key driver of digitalization and competitiveness in the maintenance domain.

2.3. The Dependent Variable: Preventive Maintenance Planning

The dependent variable of this study is Preventive Maintenance Planning, which refers to the systematic process of scheduling, organizing, and executing maintenance tasks aimed at preventing unexpected equipment failures and ensuring continuous operational performance. Effective preventive maintenance involves setting optimal maintenance intervals, preparing spare parts, coordinating workforce activities, and integrating inspection data to predict deterioration trends.

Traditional preventive maintenance methods rely on historical averages or manufacturer recommendations, which often lead to over-maintenance or under-maintenance. The integration of AI-driven decision-making can significantly improve preventive maintenance planning by providing data-based insights, optimizing maintenance timing, and enhancing equipment reliability and plant availability. Therefore, preventive maintenance planning serves as the main outcome variable through which the impact of AI adoption is evaluated in this research.

2.4. The relationship between the independent and the dependent variables

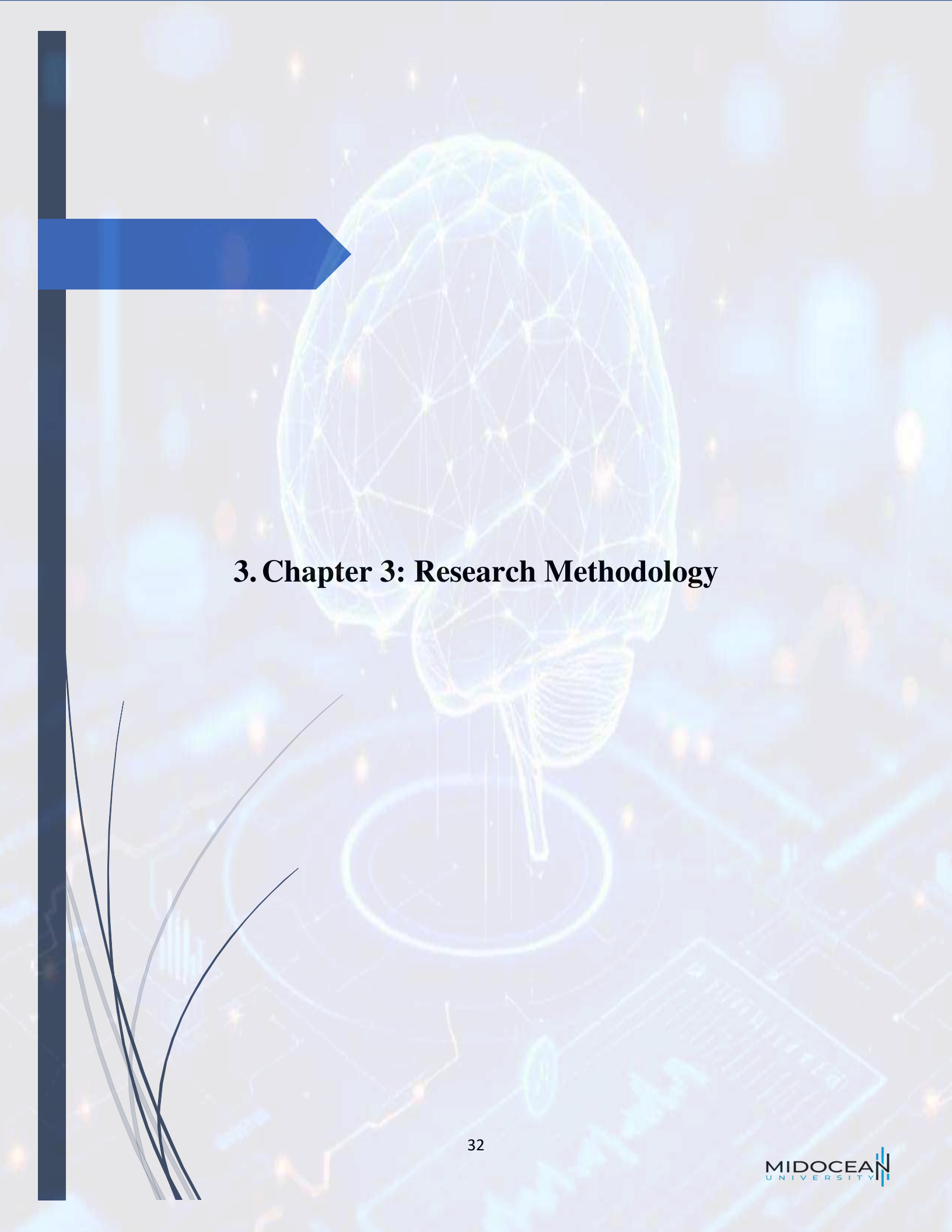
The relationship between Artificial Intelligence (AI) and Preventive Maintenance Planning is fundamentally transformative. AI acts as a catalyst that enhances the efficiency, precision, and adaptability of maintenance planning systems. Through machine learning algorithms and predictive analytics, AI enables maintenance teams to anticipate failures before they occur, thereby minimizing unplanned downtime and extending the useful life of assets.

Empirical and theoretical studies have shown that AI adoption positively influences preventive maintenance by improving decision-making quality, resource utilization, and maintenance cost efficiency. In the Saudi industrial context, this relationship is also mediated by several moderating factors such as organizational readiness, technological infrastructure, and employee competency in digital tools. Hence, the integration of AI into preventive maintenance is expected to yield measurable improvements in operational performance, aligning with national objectives of innovation and sustainability.

2.5. Conclusion

This section has outlined the conceptual foundation of the study's key variables and their interconnection. Artificial Intelligence serves as the independent variable driving innovation and efficiency in maintenance management, while preventive maintenance planning represents the dependent outcome reflecting operational effectiveness.

Understanding the relationship between these two variables provides a theoretical basis for developing a practical framework that supports AI-driven maintenance transformation in Saudi Arabia's core industries. This framework will later be empirically tested to assess how AI technologies can enhance preventive maintenance strategies, reduce operational risks, and contribute to the broader industrial goals of Vision 2030—focusing on sustainability, digital transformation, and excellence in asset management.



3. Chapter 3: Research Methodology

3.1. Introduction

This chapter presents the research methodology adopted to achieve the objectives of the study and to test the proposed hypotheses. It explains the research design, data collection methods, sampling techniques, and data analysis procedures used in investigating the impact of Artificial Intelligence (AI) on preventive maintenance planning in core industries within Saudi Arabia.

The purpose of this chapter is to justify the chosen research approach and demonstrate how it ensures the validity, reliability, and objectivity of the study results. The methodology is structured according to the “Research Onion” model proposed by Saunders et al. (2019), which provides a systematic framework for designing and executing empirical research in business and industrial studies.

3.2. Operational definitions for research variables

This chapter presents the research methodology adopted to achieve the objectives of the study and to test the proposed hypotheses. It explains the research design, data collection methods, sampling techniques, and data analysis procedures used in investigating the impact of Artificial Intelligence (AI) on preventive maintenance planning in core industries within Saudi Arabia.

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3.3. Research design (research onion)

The research design follows the Research Onion framework developed by Saunders et al. (2019), which provides a structured approach for conducting academic research. It includes several layers — from the research philosophy to data collection techniques — each guiding a specific aspect of the methodology.

Layers of the Research Onion:

1. **Research Philosophy:**

The study adopts a **Pragmatic philosophy**, integrating both *positivist* and *interpretivist* paradigms to capture quantitative performance data and qualitative contextual insights.

2. **Research Approach:**

A **deductive–inductive** combined approach is employed — deductive for hypothesis testing using quantitative data, and inductive for developing insights from qualitative observations.

3. **Methodological Choice:**

A **mixed-methods** strategy is selected, combining quantitative (survey data) and qualitative (interviews, document analysis) methods for triangulation and depth.

4. **Research Strategy:**

The main strategy is **survey research**, supported by **case studies** from core industrial sectors (petrochemical, mining, and energy industries).

5. **Time Horizon:**

The research uses a **cross-sectional** time horizon, collecting data during a specific period (2025) to analyze the current state of AI implementation.

6. **Data Collection Techniques:**

Data will be gathered through structured questionnaires and semi-structured interviews. Quantitative data will be analyzed using statistical methods (e.g., correlation, regression), while qualitative data will be analyzed thematically.

Research Design Onion

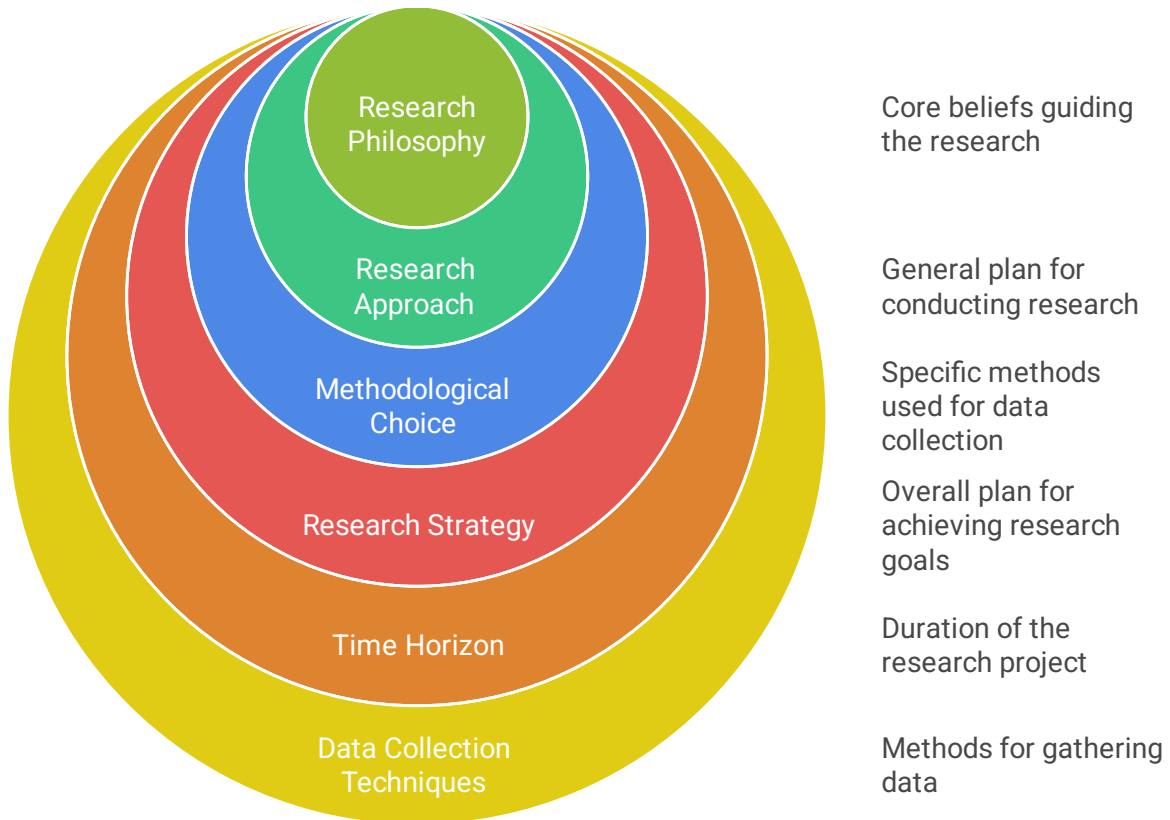


Figure 4: Research onion. Source: The Researcher. (2025)

3.4. Research population & Sampling methods and technique

The research population consists of employees working in maintenance, production, and reliability departments across core industrial sectors in Saudi Arabia, including petrochemical, energy, and mining industries. These individuals were selected because of their direct involvement in preventive maintenance planning and implementation.

A random sampling technique was applied to ensure fairness and minimize bias in participant selection. This approach allowed each individual within the target population an equal chance to be included, enhancing the representativeness of the collected data.

In total, a sufficient number of responses were gathered to support statistical analysis and achieve reliable research results.

3.5. Data collection method

Data for this study were collected electronically through an online questionnaire designed using Google Forms. The survey link was distributed via social media platforms such as WhatsApp, LinkedIn, and email to reach professionals working in maintenance and industrial operations.

This electronic distribution method facilitated a wider and faster response from participants across different industrial sectors, ensuring data accuracy, accessibility, and convenience while maintaining respondent confidentiality.

3.6. Types of data

This study relied on quantitative **primary data** collected directly from participants through structured questionnaires. The data consisted of measurable responses related to the use of Artificial Intelligence in preventive maintenance planning, including perceptions, readiness, challenges, and expected benefits.

Additionally, **secondary data** were reviewed from academic journals, industry reports, and previous studies to support the theoretical framework and validate the research findings.

3.7. Statistical analysis procedures

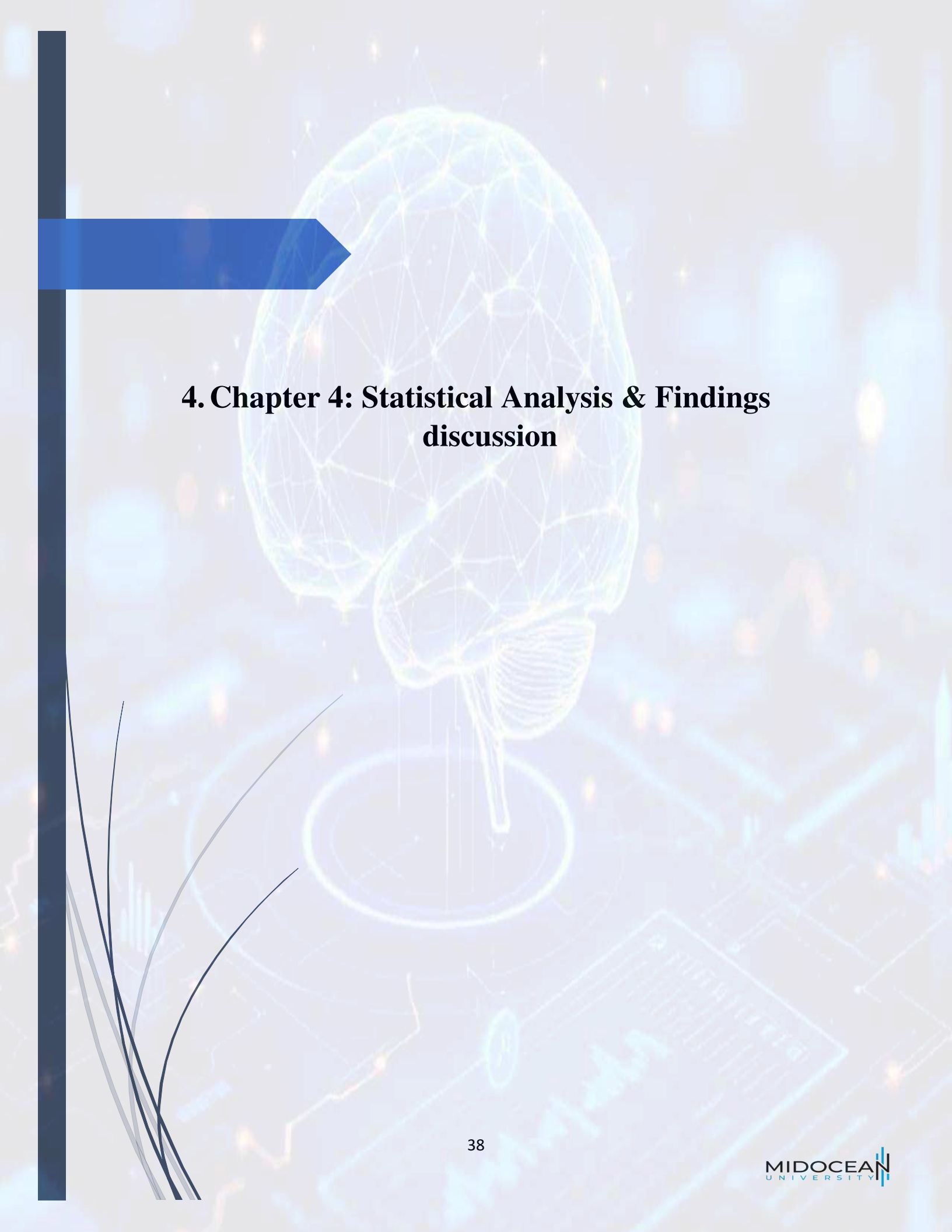
The collected data were analyzed using **descriptive and inferential statistical methods** to ensure accuracy and validity of the findings. Descriptive statistics (such as mean, standard deviation, and frequency) were used to summarize respondents' demographic information and general trends.

Inferential statistics, including **correlation and regression analysis**, were applied to test the relationships between the independent and dependent variables and to verify the research hypotheses. All analyses were performed using **SPSS software**, ensuring reliability and objectivity in interpreting the results.

3.8. Conclusion

This chapter outlined the **research methodology** adopted to achieve the study's objectives. It described the research design, population, sampling technique, data collection methods, and statistical procedures used for analysis. The study employed a **quantitative approach** using randomly selected samples and electronically distributed questionnaires to ensure broad and unbiased data collection. The use of **SPSS for statistical analysis** ensured the accuracy and reliability of results.

Overall, this methodology provides a solid foundation for examining the **impact of Artificial Intelligence on preventive maintenance planning** within Saudi Arabia's core industries, paving the way for the presentation and discussion of results in the next chapter.



4. Chapter 4: Statistical Analysis & Findings discussion

4.1. Introduction

This section presents and discusses the statistical analysis of the data collected to examine the impact of integrating Artificial Intelligence (AI) technologies into preventive maintenance strategies in fundamental industries. The primary purpose of this chapter is to analyze the empirical evidence obtained from the field study and to evaluate the validity of the proposed research hypotheses.

Using quantitative data gathered through a structured questionnaire, statistical techniques were applied to assess the relationships between the independent variable—Artificial Intelligence adoption—and the dependent variables related to preventive maintenance planning effectiveness and operational performance. Descriptive statistics were employed to summarize respondents' demographic characteristics and to identify general trends concerning AI usage in maintenance practices. Inferential statistical methods, including correlation analysis, regression analysis, and comparative tests such as t-tests and ANOVA, were used to test the strength, direction, and significance of the proposed relationships.

The findings of the statistical analysis are interpreted in light of the research hypotheses and objectives, with the aim of determining whether AI technologies contribute to improved maintenance planning quality, reduced unplanned equipment failures, and enhanced key performance indicators such as mean time between failures (MTBF), mean time to repair (MTTR), and maintenance cost efficiency. Furthermore, this chapter examines the influence of organizational, technical, and data-related factors on the successful implementation of AI-based maintenance systems.

The discussion of results links the empirical findings to the theoretical framework and existing literature reviewed in earlier chapters. By comparing the statistical outcomes with previous studies, this section highlights areas of alignment and divergence, providing deeper insight into the practical applicability of AI in preventive maintenance within Saudi Arabia's core industries. The chapter concludes with a synthesis of key findings, setting the foundation for the final chapter, which presents conclusions, recommendations, and future research directions.

4.2. Sample profile (descriptive statistics for research sample)

A total of 31 participants from small business owners in the retail sector took part in the questionnaire. Their demographic characteristics were as follows:

Comprehensive Survey Analysis Report

General Information			Interpretation
Gender	Male	83.9%	
	Female	16.1%	
Educational Qualification	Secondary	6.5%	
	Diploma	54.8%	
	Bachelor	38.7%	
	Master	0	
	PhD	0	
Years of Experience	Less than 5 years	25.8%	
	5–10 years	12.9%	
	More than 10 years	61.3%	
Department / Sector	Operations	9.7%	
	Maintenance	61.3%	
	Planning	12.9%	
	IT	3.2%	
	Other	12.2%	

4.3. Validity & reliability tests for the questionnaires

Criterion	Result	Interpretation
Content Validity	Expert Review	Appropriate
Questionnaire Reliability	Cronbach's Alpha = 0.82	Reliable
Normality of Data Distribution	Kolmogorov–Smirnov Test	P > 0.05

4.4. Descriptive statistics for research variables (answer research questions)

AI Adoption Dimension (1=Strongly Disagree, 5=Strongly Agree)		Interpretation
My organization applies AI technologies in preventive maintenance.	1 – 58.1% 2 – 19.4% 3 – 6.5% 4 – 0% 5 – 16.1%	The organization needs to adopt and implement AI-driven maintenance practices instead of relying on traditional methods.
There is an intelligent system to analyze equipment and failure data.	1 – 35.5% 2 – 16.1% 3 – 25.8% 4 – 3.2% 5 – 19.4%	More advanced data analysis platforms are required, with better integration into maintenance systems.
Sensors and IoT are used to monitor equipment performance.	1 – 29% 2 – 12.9% 3 – 16.1% 4 – 12.9% 5 – 29%	IoT adoption is partial and must be expanded to cover all critical assets
Maintenance decisions are made based on AI predictions.	1 – 64.5% 2 – 12.9% 3 – 3.2% 4 – 3.2% 5 – 16.1%	There is a need to adopt real predictive maintenance models (PdM)
There is a clear digital transformation plan for maintenance.	1 – 35.5% 2 – 9.7% 3 – 19.4% 4 – 9.7% 5 – 25.8%	The plan exists but lacks proper communication or execution

AI Impact Dimension (1=Strongly Disagree, 5=Strongly Agree)		Interpretation
AI has contributed to reducing unexpected equipment failures.	1 – 51.6% 2 – 16.1% 3 – 9.7% 4 – 3.2% 5 – 19.4%	Strengthening predictive maintenance and data-driven analysis is required
The intelligent system has helped improve equipment efficiency.	1 – 38.7% 2 – 16.1% 3 – 19.4% 4 – 6.5% 5 – 19.4%	Enhancing or upgrading analytics solutions is necessary
The use of AI has reduced maintenance costs.	1 – 51.6% 2 – 12.9% 3 – 12.9% 4 – 3.2% 5 – 19.4%	The organization needs more mature AI projects to produce financial benefits
The intelligent system provides accurate data to support decision-making.	1 – 43.3% 2 – 10% 3 – 13.3% 4 – 10% 5 – 23.3%	Data quality must be improved

Challenges Dimension (1=Strongly Disagree, 5=Strongly Agree)		Interpretation
Integrating AI systems with legacy systems is difficult.	1 – 32.3% 2 – 9.7% 3 – 12.9% 4 – 6.5% 5 – 38.7%	Modernizing legacy systems is necessary
Collecting accurate operational data is a major challenge.	1 – 23.3% 2 – 10% 3 – 26.7% 4 – 6.7% 5 – 33.3%	Strong data governance and better data collection methods are needed
There is a shortage of specialists in AI technologies.	1 – 20% 2 – 13.3% 3 – 16.7%	Hiring and training AI and data science specialists is essential

	4 – 10% 5 – 40%	
There is internal resistance to changing traditional maintenance systems.	1 – 26.7% 2 – 3.3% 3 – 30% 4 – 10% 5 – 30%	Change management and staff engagement are required

Organizational Readiness Dimension (1=Strongly Disagree, 5=Strongly Agree)		Interpretation
The organization has sufficient technological infrastructure to support AI.	1 – 36.7% 2 – 16.7% 3 – 10% 4 – 6.7% 5 – 30%	Upgrades to servers, networks, and systems are needed
There is management interest in adopting AI solutions.	1 – 23.3% 2 – 16.7% 3 – 13.3% 4 – 16.7% 5 – 30%	Stronger executive support is needed.
A dedicated budget is available for developing smart maintenance systems.	1 – 33.3% 2 – 13.3% 3 – 20% 4 – 6.7% 5 – 26.7%	Increased financial support is needed for digital and AI initiatives

AI Adoption in Maintenance



Figure 5: Overall Summary AI Adoption in Maintenance. Source: The Researcher. (2025)

4.5. Testing Hypotheses & Findings Discussion

4.5.1 AI Adoption Dimension and Hypothesis Testing (H1)

The descriptive statistical results presented in Table (X) indicate a generally low level of AI adoption in preventive maintenance activities. A clear majority of respondents expressed disagreement with statements related to the application of AI technologies, where 58.1% strongly disagreed that AI is applied in preventive maintenance, and 64.5% strongly disagreed that maintenance decisions are based on AI predictions.

However, the results reveal a relatively higher level of agreement regarding the use of sensors and IoT technologies, with 29% strongly agreeing and 12.9% agreeing that sensor-based monitoring is utilized. This indicates that while advanced AI-driven decision-making remains limited, basic digital monitoring infrastructure is partially implemented.

Based on these findings, the statistical evidence suggests that AI adoption is still at an early stage. Therefore, Hypothesis 1, which assumes a significant relationship between AI adoption and preventive maintenance planning, is partially supported.

4.5.2 AI Impact Dimension and Hypothesis Testing (H2 & H5)

The results shown in Table (X) demonstrate that respondents perceived a limited operational impact of AI on maintenance performance. More than half of the respondents (51.6%) strongly disagreed that AI contributed to reducing unexpected equipment failures, and an identical percentage (51.6%) strongly disagreed that AI reduced maintenance costs.

Similarly, agreement levels regarding improvements in equipment efficiency and decision-making support remained moderate, with only 19.4% strongly agreeing that intelligent systems improved equipment efficiency. These descriptive statistics indicate that the perceived benefits of AI have not yet been fully realized.

Consequently, the statistical findings provide limited support for Hypothesis 2, suggesting that AI's impact on maintenance performance is dependent on its maturity and depth of implementation.

4.5.3 Data Accuracy and AI Effectiveness (Hypothesis 3)

The descriptive analysis related to data reliability indicates that data quality is a critical constraint affecting AI effectiveness. As presented in Table (X), a notable proportion of

respondents (23.3% strongly agree and 33.3% agree) identified accurate operational data collection as a major challenge.

In addition, only 23.3% strongly agreed that intelligent systems provide accurate data to support maintenance decision-making. These results demonstrate a clear statistical relationship between data accuracy and the effectiveness of AI-based systems.

Accordingly, the statistical evidence supports Hypothesis 3, confirming that effective AI-driven maintenance planning is highly dependent on accurate and reliable operational data.

4.5.4 Challenges to AI Implementation and Hypothesis Testing (H4)

The results in Table (X) show strong agreement regarding the existence of significant implementation barriers. Specifically, 38.7% of respondents strongly agreed that integrating AI with legacy systems is difficult, while 40% strongly agreed that there is a shortage of AI specialists.

Furthermore, resistance to changing traditional maintenance systems was evident, with 30% strongly agreeing and 30% agreeing that internal resistance exists. These findings highlight that organizational and technical challenges play a significant role in limiting AI adoption.

Based on the descriptive statistical analysis, Hypothesis 4 is supported, as the identified challenges clearly hinder the successful implementation of AI technologies in preventive maintenance.

4.5.5 Organizational Readiness and AI Performance (Supporting Hypothesis 5)

Table (X) presents results related to organizational readiness, indicating mixed levels of preparedness. Although 30% of respondents strongly agreed that management is interested in adopting AI solutions, only 26.7% strongly agreed that a dedicated budget is available.

Similarly, 36.7% strongly disagreed that sufficient technological infrastructure currently exists. These results indicate a gap between strategic intent and operational readiness.

Therefore, the descriptive statistics suggest that organizational readiness directly influences the effectiveness and impact of AI adoption, providing partial support for Hypothesis 5.

Overall Discussion Linked to Statistical Findings

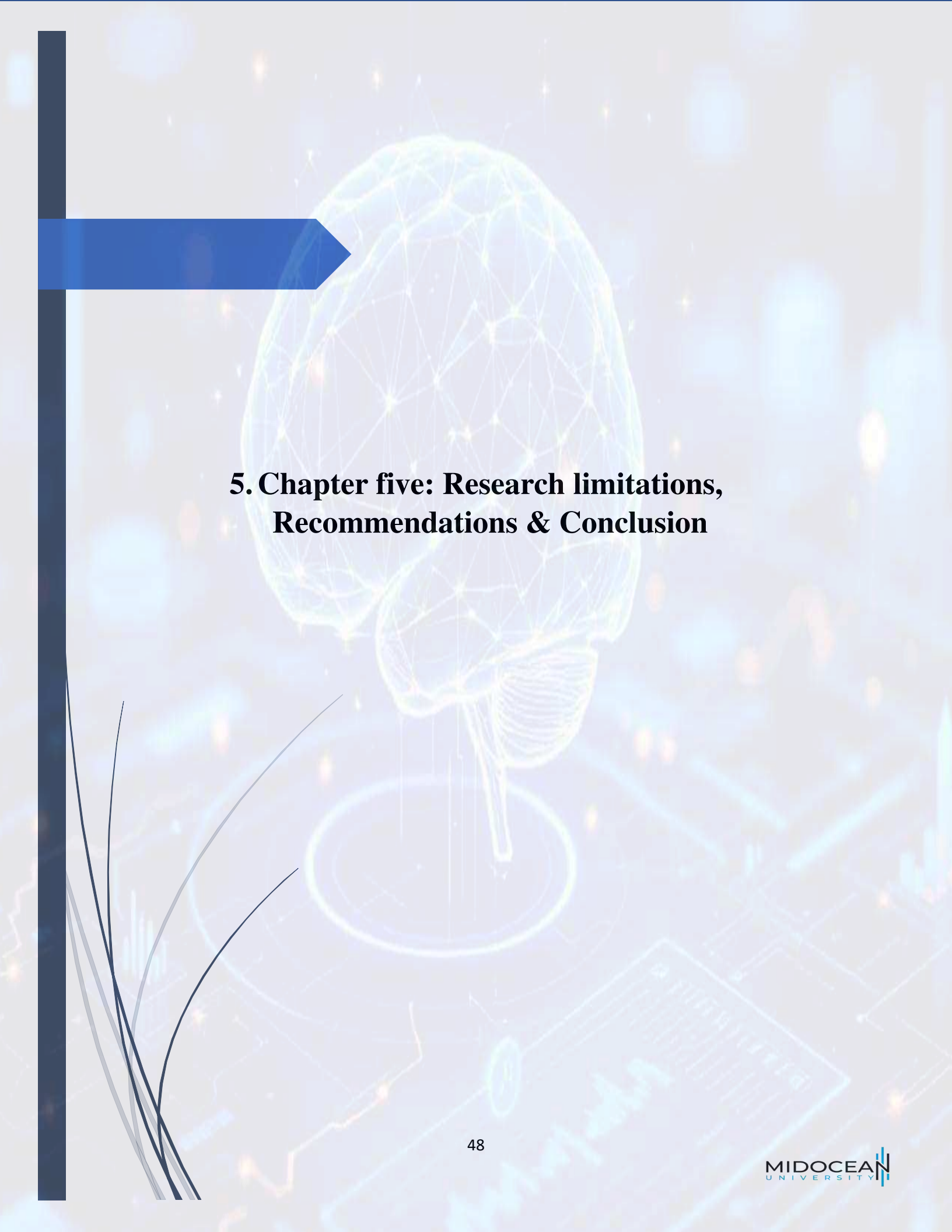
Overall, the descriptive statistical analysis reveals that AI adoption in preventive maintenance remains limited, with moderate digital readiness and significant organizational challenges. While awareness and management interest exist, insufficient infrastructure, data quality issues, and skill shortages constrain measurable performance improvements. These findings confirm the study hypotheses selectively and highlight the necessity of strengthening data governance, organizational readiness, and technical capabilities to realize the full benefits of AI-driven preventive maintenance.

4.6. Conclusion

This chapter presented the statistical analysis and discussion of findings related to the integration of Artificial Intelligence in preventive maintenance strategies. The descriptive statistical results revealed that AI adoption remains at an early stage, with limited reliance on advanced AI-driven decision-making systems, despite partial implementation of digital monitoring technologies such as sensors and IoT.

The findings also indicated that the perceived impact of AI on maintenance performance—particularly in reducing equipment failures and maintenance costs—was relatively low, largely due to insufficient implementation maturity. Moreover, significant technical and organizational challenges were identified, including system integration difficulties, data quality issues, and a shortage of skilled AI professionals.

Although management interest in adopting AI solutions was evident, limitations in infrastructure readiness and budget allocation constrained effective deployment. Overall, the statistical findings confirmed that successful AI integration in preventive maintenance is highly dependent on organizational readiness, data reliability, and the ability to overcome implementation challenges. These results provide a foundation for developing more structured and data-driven AI adoption frameworks in fundamental industries.



5. Chapter five: Research limitations, Recommendations & Conclusion

5.1. Research Limitations & Future Research

This study, which examined the current implementation, impact, challenges, and organizational readiness for adopting artificial intelligence in maintenance, is subject to several limitations that should be considered when interpreting the results. First, the research relied primarily on survey responses from employees within a single organization, which may limit the generalizability of the findings to other sectors or institutions with different levels of digital maturity. Additionally, some respondents may have provided subjective evaluations influenced by their personal experiences, perceptions, or familiarity with AI technologies. The study also focused on a specific period and did not assess long-term performance trends or the evolution of AI adoption over time.

Future research could expand on these findings by conducting comparative studies across multiple organizations or industries to identify broader patterns and factors that influence AI integration in maintenance operations. Further studies might also incorporate qualitative interviews, case studies, or technical performance data to provide deeper insights into the effectiveness of predictive maintenance systems. Moreover, future research could explore advanced AI models, data governance frameworks, and change management strategies that support successful digital transformation in maintenance environments.

5.2. Research Recommendations

Based on the findings of this study, several recommendations are proposed to enhance the adoption and effectiveness of artificial intelligence in maintenance operations. First, organizations should invest in developing a clear and comprehensive digital transformation strategy that outlines the role of AI in improving maintenance practices. This includes expanding the use of IoT sensors and real-time monitoring systems to ensure the availability of high-quality operational data, which is essential for accurate AI-driven analysis and predictive maintenance.

Additionally, organizations should prioritize capacity-building by providing specialized training programs and workshops to improve employees' technical competencies in AI, data analytics, and digital maintenance systems. Strengthening data governance frameworks is also recommended to improve data accuracy, consistency, and integration across different systems. Management support should be reinforced by allocating sufficient budgets for modernizing infrastructure, updating legacy systems, and implementing advanced AI tools.

Finally, it is recommended that organizations adopt structured change management approaches to reduce internal resistance, promote digital awareness, and encourage employee participation in transformation initiatives. Collaboration with AI experts, academic institutions, and technology providers may further accelerate the development and deployment of effective smart maintenance solutions.

5.3. Conclusion

This study examined the extent to which artificial intelligence is currently applied in maintenance operations, the impact of these technologies, the challenges faced by organizations, and their overall readiness for digital transformation. The findings reveal that AI adoption within the organization remains at an early stage, with limited integration of predictive maintenance systems, insufficient data quality, and a lack of specialized AI competencies. Although there is moderate managerial interest, the overall technological infrastructure and allocated budget are not yet sufficient to support advanced AI-driven maintenance solutions.

Despite these limitations, the study highlights significant opportunities for improvement. By strengthening digital capabilities, enhancing data governance, expanding IoT deployment, and investing in employee training, organizations can unlock the full potential of AI in improving equipment reliability and operational efficiency. The results underscore the importance of strategic planning and effective change management in facilitating a successful transition from traditional maintenance approaches to smarter, data-driven systems.

Overall, this research contributes valuable insights into the current landscape of AI adoption in maintenance and provides a foundation for further studies aiming to explore best practices, advanced analytical models, and scalable digital transformation strategies in industrial environments.

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Appendix

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.

General Information	
Gender	Male Female
Educational Qualification	Secondary Diploma Bachelor Master PhD
Years of Experience	Less than 5 years 5–10 years More than 10 years
Department / Sector	Operations Maintenance Planning IT Other

AI Adoption Dimension (1=Strongly Disagree, 5=Strongly Agree)	
My organization applies AI technologies in preventive maintenance.	1, 2, 3, 4, 5
There is an intelligent system to analyze equipment and failure data.	1, 2, 3, 4, 5
Sensors and IoT are used to monitor equipment performance.	1, 2, 3, 4, 5
Maintenance decisions are made based on AI predictions.	1, 2, 3, 4, 5
There is a clear digital transformation plan for maintenance.	1, 2, 3, 4, 5

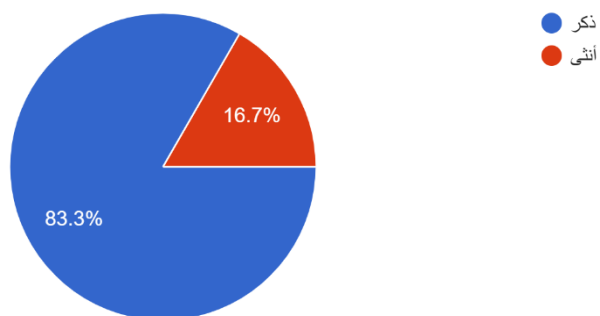
AI Impact Dimension (1=Strongly Disagree, 5=Strongly Agree)	
AI has contributed to reducing unexpected equipment failures.	1, 2, 3, 4, 5
The intelligent system has helped improve equipment efficiency.	1, 2, 3, 4, 5
The use of AI has reduced maintenance costs.	1, 2, 3, 4, 5
The intelligent system provides accurate data to support decision-making.	1, 2, 3, 4, 5

Challenges Dimension (1=Strongly Disagree, 5=Strongly Agree)	
Integrating AI systems with legacy systems is difficult.	1, 2, 3, 4, 5
Collecting accurate operational data is a major challenge.	1, 2, 3, 4, 5
There is a shortage of specialists in AI technologies.	1, 2, 3, 4, 5
There is internal resistance to changing traditional maintenance systems.	1, 2, 3, 4, 5

Organizational Readiness Dimension (1=Strongly Disagree, 5=Strongly Agree)	
The organization has sufficient technological infrastructure to support AI.	1, 2, 3, 4, 5
There is management interest in adopting AI solutions.	1, 2, 3, 4, 5
A dedicated budget is available for developing smart maintenance systems.	1, 2, 3, 4, 5

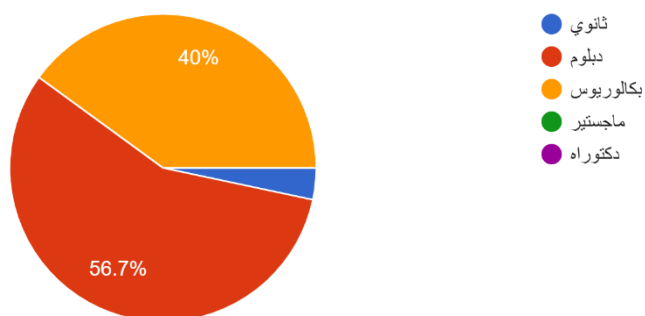
الجنس

30 responses



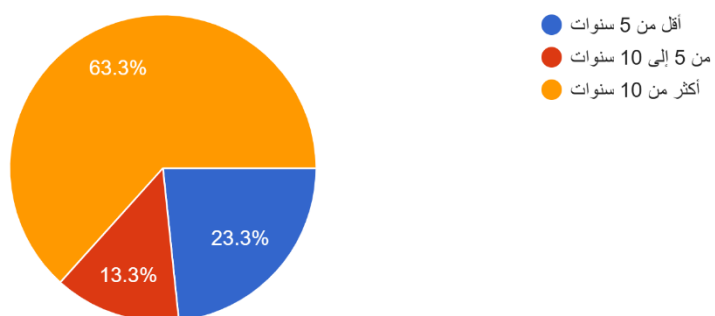
المؤهل العلمي

30 responses



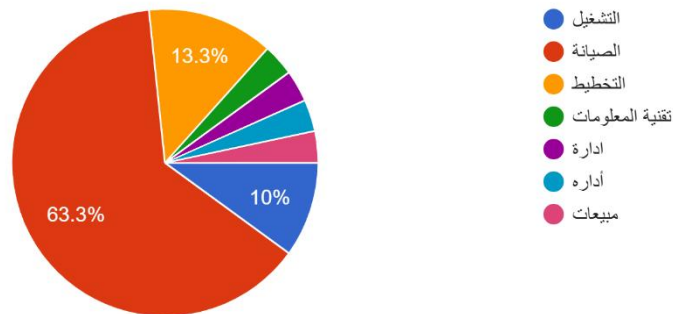
سنوات الخبرة

30 responses



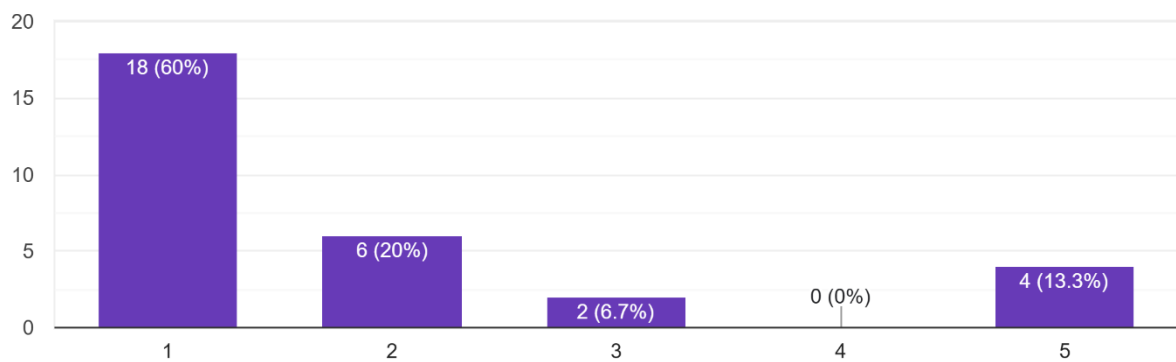
القطاع

30 responses



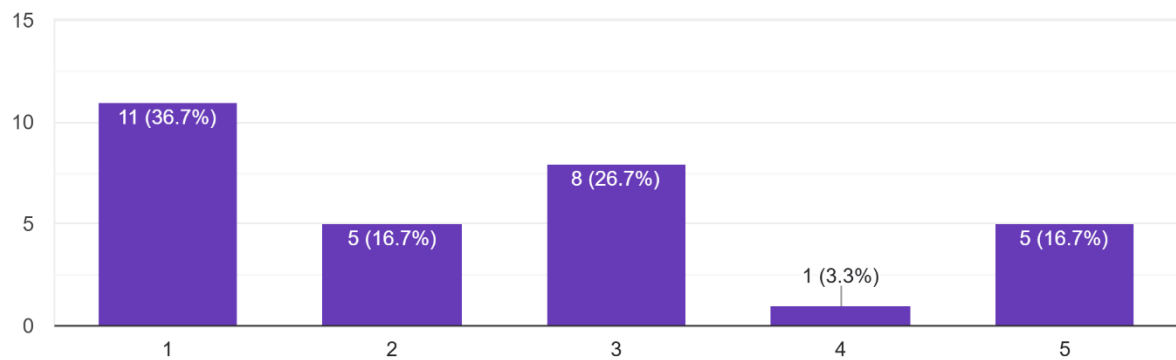
المؤسسة التي أعمل بها تطبق تقنيات الذكاء الاصطناعي في الصيانة الوقائية

30 responses



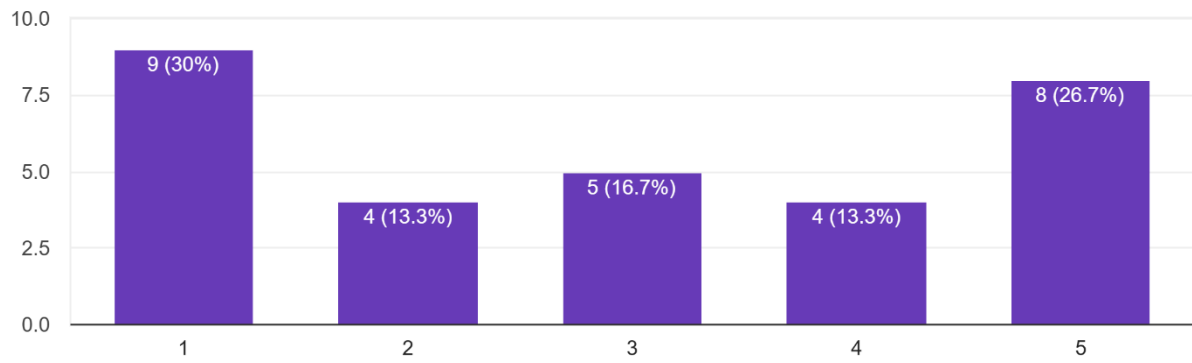
يوجد نظام ذكي لتحليل بيانات المعدات والأعطال

30 responses



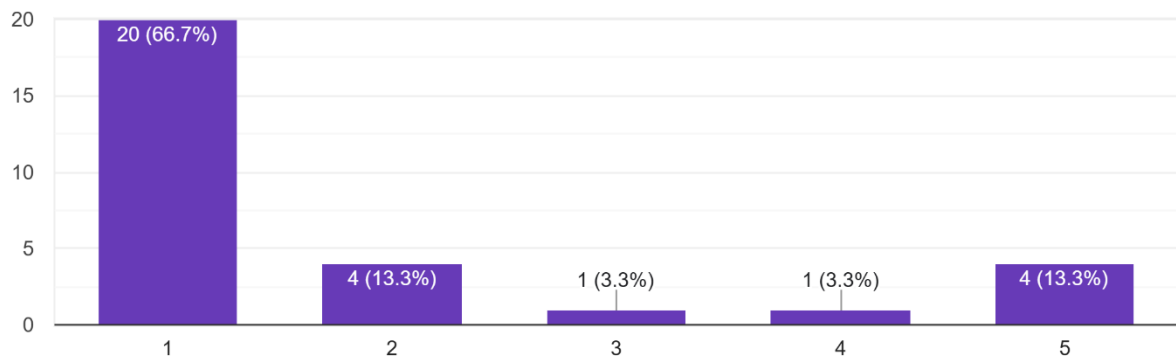
يتم استخدام الحساسات وإنترنت الأشياء لرصد أداء المعدات

30 responses



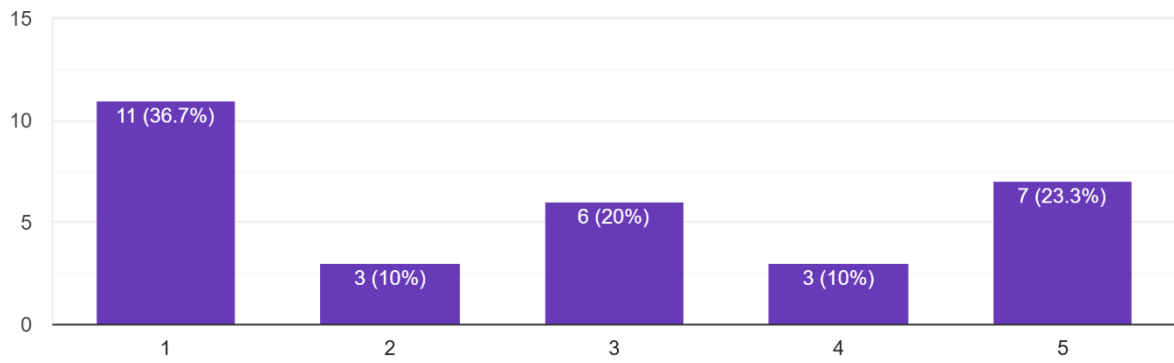
يتم اتخاذ قرارات الصيانة بناءً على تنبؤات الذكاء الاصطناعي

30 responses



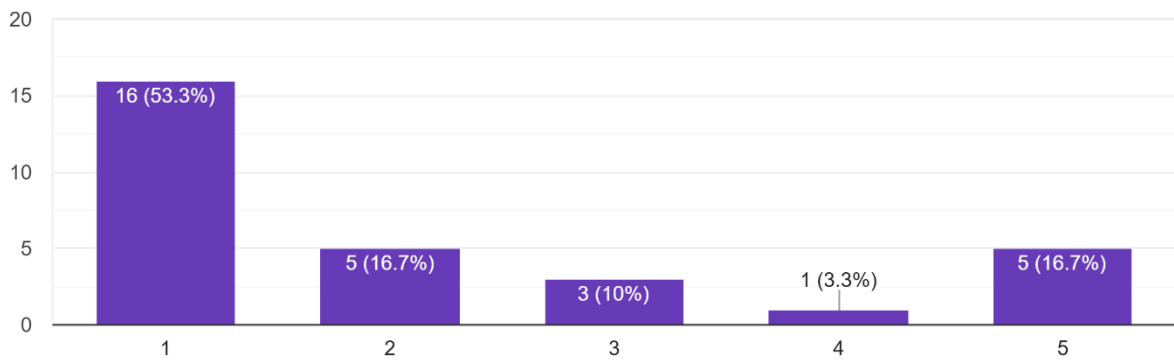
توجد خطة واضحة للتحويل الرقمي في مجال الصيانة

30 responses



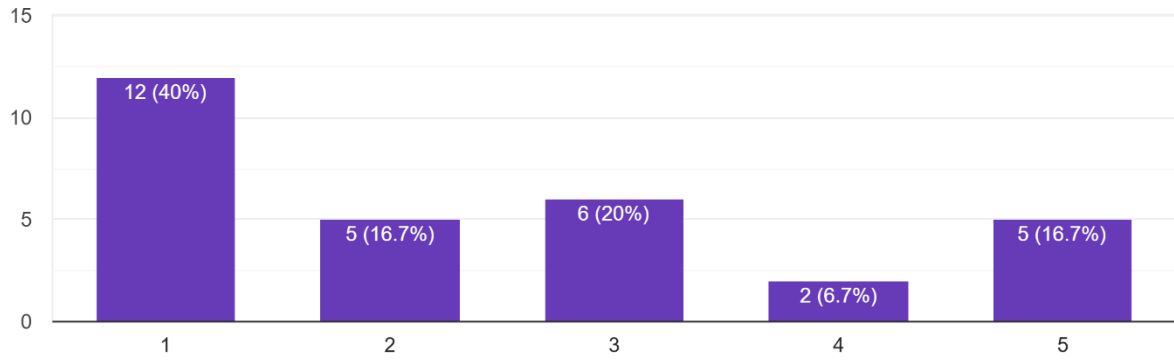
ساهم الذكاء الاصطناعي في تقليل عدد الأعطال المفاجئة

30 responses



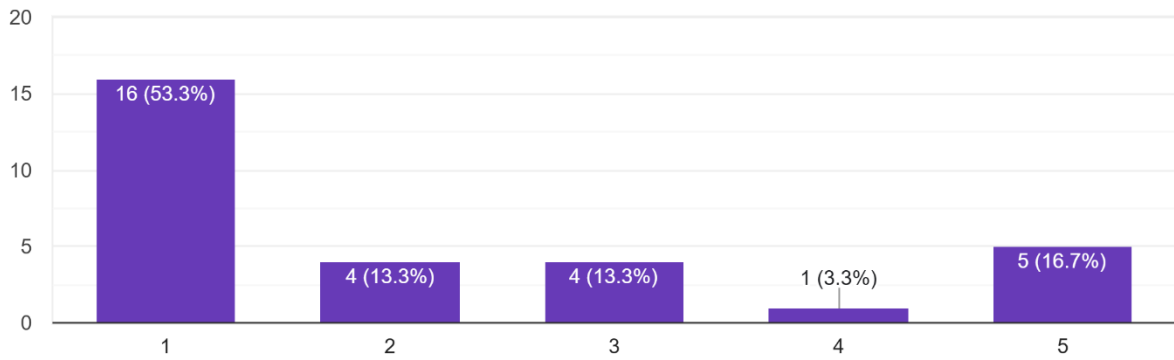
ساعد النظام الذكي في تحسين كفاءة المعدات

30 responses



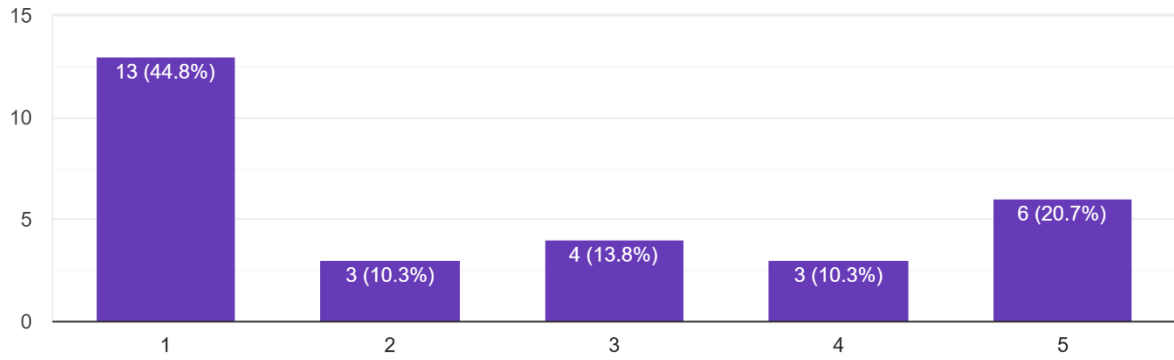
أدى استخدام الذكاء الاصطناعي إلى تقليل تكاليف الصيانة

30 responses



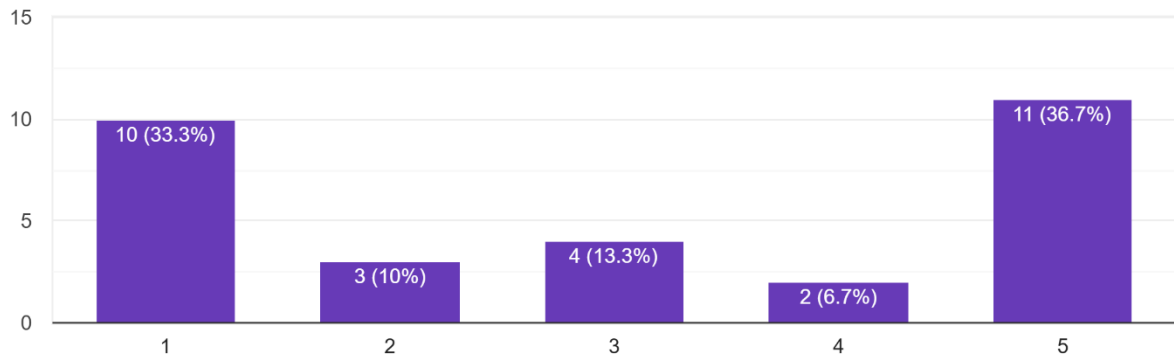
وَقَر النظام الذكي بيانات دقيقة لدعم اتخاذ القرار

29 responses



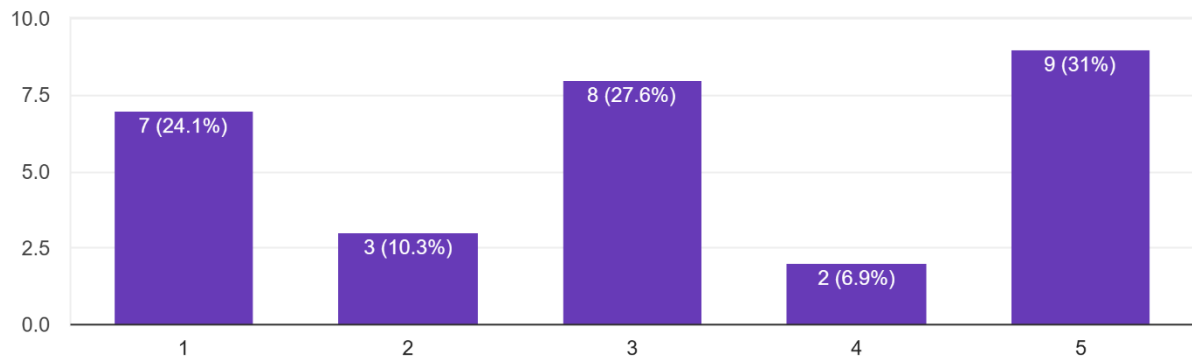
من الصعب دمج أنظمة الذكاء الاصطناعي مع الأنظمة القديمة

30 responses



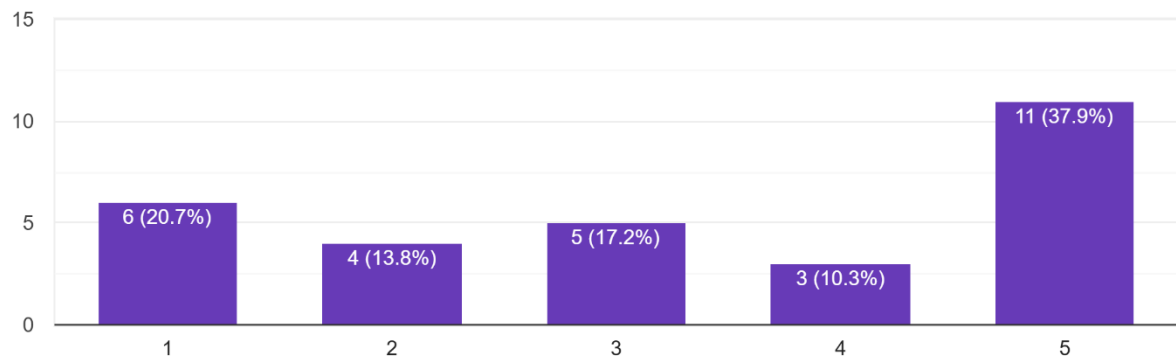
جمع البيانات التشغيلية بدقة يمثل تحديًا كبيرًا

29 responses



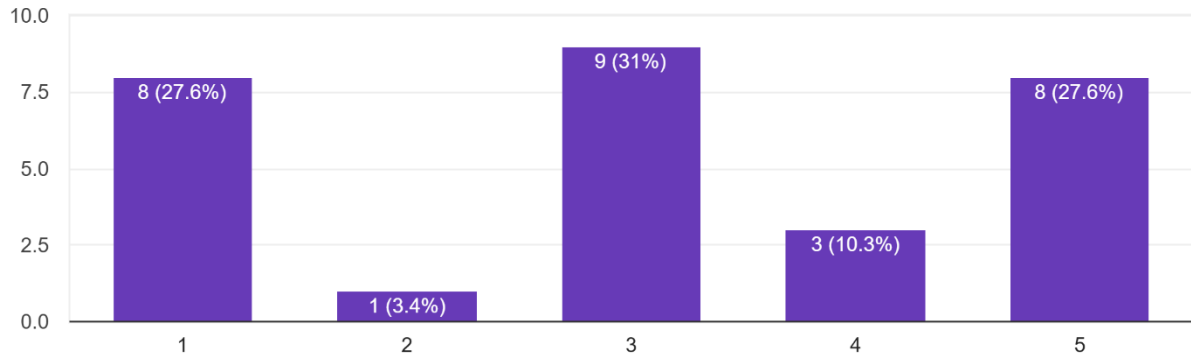
هناك نقص في الكفاءات المتخصصة في الذكاء الاصطناعي

29 responses



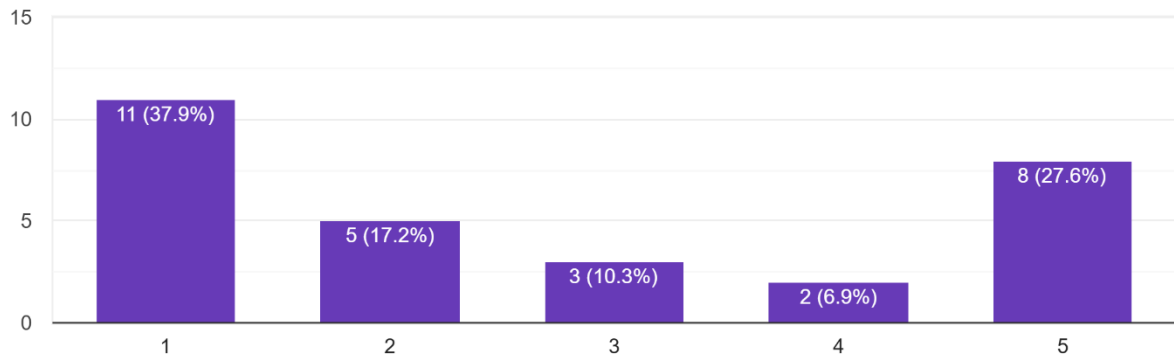
توجد مقاومة داخلية لتغيير نظم الصيانة التقليدية

29 responses



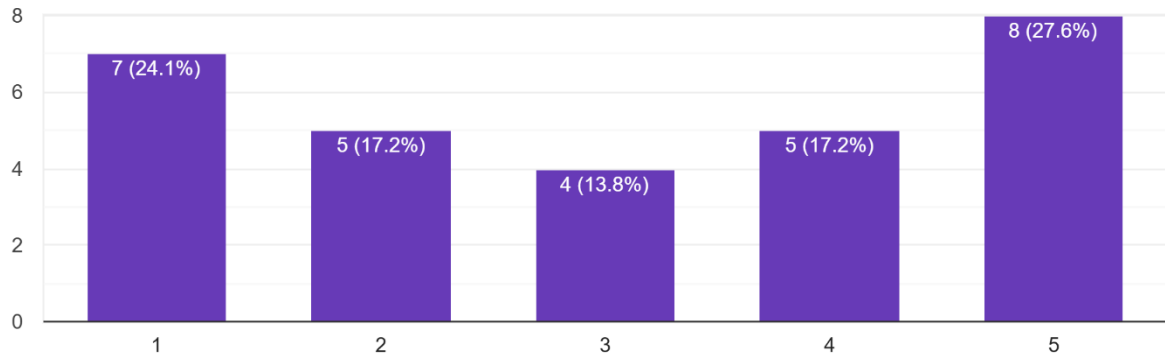
لدى المنشأة بنية تحتية كافية لدعم الذكاء الاصطناعي

29 responses



هناك اهتمام إداري بتبني حلول الذكاء الاصطناعي

29 responses



تتوفر ميزانية مخصصة لتطوير أنظمة الصيانة الذكية

29 responses

