Factors Influencing the Adoption and Implementation of Predictive Maintenance Technologies in Organizations

العوامل المؤثرة في تبني وتطبيق تقنيات الصيانة الوقائية في المؤسسات

by

MOHAMMED FADHL MOHAMMED AL NASHWAN

Dissertation submitted in partial fulfilment

of the requirements for the degree of

MSc ENGINEERING MANAGEMENT

at

The British University in Dubai

August 2023

DECLARATION

I warrant that the content of this research is the direct result of my own work and that any use made in it of published or unpublished copyright material falls within the limits permitted by international copyright conventions.

I understand that a copy of my research will be deposited in the University Library for permanent retention.

I hereby agree that the contents of this dissertation for which I am author and copyright holder may be copied and distributed by The British University in Dubai for the purposes of research, private study or education and that The British University in Dubai may recover from purchasers the costs incurred in such copying and distribution, where appropriate.

I understand that The British University in Dubai may make a digital copy available in the institutional repository.

I understand that I may apply to the University to retain the right to withhold or to restrict access to my thesis for a period which shall not normally exceed four calendar years from the congregation at which the degree is conferred, the length of the period to be specified in the application, together with the precise reasons for making that application.

____

Signature of the student

COPYRIGHT AND INFORMATION TO USERS

ABSTRACT

Significant research has explored the numerous advantages of predictive maintenance technologies. In today's Industry 4.0 era, organizations, especially in the manufacturing sector, are increasingly adopting predictive maintenance practices and technologies to forecast equipment failure enabling them to proactive maintain manufacturing and processing tasks and activities. Predictive maintenance technologies enable organizations to meet their production costs as well as product quality and quantity objectives. Accordingly, studies have associated predictive maintenance technologies and practices with the capabilities of improving organizational performance in the economic, ecological/environmental, and social dimensions. However, despite the numerous advantages, many organizations have not leveraged these technologies due to various organizational, financial, and human-related barriers. As a result, drawing from relevant literature and the data from the Abu Dhabi National Oil Company (ADNOC), the study will explore the factors that influence the adoption of predictive maintenance technologies, the consequent impact on organizational performance and provide suggestions for businesses looking to adopt and use these technologies. In a questionnaire conducted with 108 respondents from different companies in the UAE, relevant insights are found pertaining to the factors that influence the adoption and implementation of predictive maintenance technologies in organizations. One of the most important factors reported by participants in this study is the user perception factor, which reflects important perceptions about the implementation of specific technologies to improve organizational performance. Another relevant factor discussed in the study is the job effectiveness factor.

ABSTRACT (in Arabic)

استكشف البحث مزايا عديدة لتقنيات الصيانة الوقائية. في عصر الصناعة 4.0 اليوم، تتبنى المؤسسات خاصة في قطاع التصنيع، ممارسات وتقنيات الصيانة الوقائية للتنبؤ بفشل المعدات، لتمكينها من الحفاظ على مهام وأنشطة التصنيع والمعالجة بشكل استباقي. تمكن تقنيات الصيانة الوقائية المؤسسات من تلبية تكاليف الإنتاج وكذلك جودة المنتج وأهداف الكمية. وفقًا لذلك، ربطت الدراسات تقنيات وممارسات الصيانة الوقائية بقدرات تحسين الأداء التنظيمي في المجالات الاقتصادية والبيئية والاجتماعية. مع ذلك، على الرغم من المزايا العديدة، لم تستغل العديد من المؤسسات هذه التقنيات بسبب العديد من الحواجز التنظيمية والمالية والبشرية. نتيجة لذلك، بالاعتماد على البحوث ذات الصلة والبيانات من شركة بترول أبوظبي الوطنية (أدنوك)، ستستكشف الدراسة العوامل التي تؤثر على اعتماد تقنيات الصيانة الوقائية، والأثر المترتب على ذلك على أداء المؤسسة وتقديم اقتراحات للشركات التي تتطلع إلى اعتماد واستخدام هذه التقنيات. في استبيان تم إجراؤه مع 108 مشاركين من شركات مختلفة في الإمارات العربية المتحدة، تم العثور على رؤى ذات صلة تتعلق بالعوامل التي تؤثر على اعتماد وتنفيذ تقنيات الصيانة التنبؤية في المؤسسات. أحد أهم العوامل التي أبلغ عنها المشاركون في هذه الدراسة هو عامل إدراك المستخدم، والذي يعكس تصورات مهمة حول تنفيذ تقنيات معينة لتحسين أداء المؤسسة. عامل آخر ذو صلة تمت مناقشته في الدراسة هو عامل فعالية الوظيفة.

ACKNOWLEDGEMENTS

I would like to acknowledge and give my warmest thanks to my supervisor Dr Saed Salhieh who made this work possible. His guidance and advice carried me through all the stages of writing my dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Introduction

1.1 INTRODUCTION

Predictive maintenance (PdM) is a top priority in today's business organizations, including manufacturing industries. Bousdekis et al. (2019) describe predictive maintenance as a contemporary approach to maintenance control that uses Industry 4.0 technologies, i.e., data analytics and machine learning technologies/methods to forecast equipment failure before it happens, allowing for proactive maintenance of tasks. PdM comprises the synchronisation of administrative and technical procedures, with the goal of ensuring that the manufacturing or supply chain systems of an industry are not compromised in any way. As Karuppiah et al. (2021) show, predictive maintenance is related to the concept of sustainable development, whereby organizations with the realization of the importance of sustainability are adopting it due to recognizing the benefits of sustainability. Such organizations are focused on incorporating sustainability in every operation or activity including manufacturing and supply chain. Besides, manufacturers increasingly perceive predictive maintenance as a core business function since the failure of critical assets is among the most significant risks to operational performance. Thus, selecting a suitable maintenance strategy is crucial for manufacturing industries and other business organizations as it promotes the company's cost reduction objectives, product quality, and quantity. Therefore, a company's maintenance practices combine organizational and technical tasks or activities aimed at maintaining equipment or machines or keeping them in a reliable working state.

Industries need to adopt sustainable maintenance practices in the manufacturing sector to support sustainable manufacturing. Franciosi et al. (2020) show that companies that neglect to adopt sustainable maintenance concepts, including predictive maintenance, are most likely to significantly affect their production volumes, asset performance, machine/equipment availability, finished product quality, employees and end-users' health and safety, social welfare as well as surrounding natural environment. Notably, the previous focus on sustainable maintenance was on design and manufacturing; however, today's companies and business organizations increasingly adopt the sustainability concept in maintenance practices.

Accordingly, sustainability maintenance practices, supported by predictive maintenance technologies, improve industrial and organizational performance in economic, ecological/environmental, and social dimensions. As Bousdekis et al. (2019) demonstrates, predictive maintenance technologies and strategies provide manufacturers with numerous competitive advantages, including maximized equipment or machine lifetime, reduced maintenance costs and downtimes, improved workplace safety, efficient adoption of maintenance resources, and flexible and optimized planning of processes. However, according to Bousdekis et al. (2019), despite the advantages of incorporating sustainable practices in an organization's maintenance activities, there is a general lack of awareness among the industrial community regarding the impact of predictive maintenance among other sustainable practices in socially responsible development or progress. In particular, most industrial stakeholders and companies primarily focus on the technical and economic aspects, neglecting the environmental component, safety issues, and quality factors.

The Abu Dhabi National Oil Company (ADNOC) is a good example of a United Arab Emirates (UAE) Company implementing the predictive maintenance concept and technologies. The large-scale and multi-year predictive maintenance project of ADNOC, the state-owned petroleum/oil and gas, aimed at maximizing the asset efficiency of the Company's upstream and downstream operations (NS Energy, 2020). ADNOC's project encompassing the monitoring and modeling of over 160 major turbines, motors, centrifugal pumping systems, and compressors would enable the central monitoring of up to 2,500 critical machines. On the other hand, Bousdekis et al. (2019) describe the industry's numerous cases of predictive maintenance solutions. First, predictive maintenance in offshore oil drilling led to a 38% reduction in maintenance costs and a significant safety improvement. Secondly, the predictive maintenance-enabled anomaly detection in moulding machines in the automotive industry increased knowledge on the defects' root causes and a scrap rate improvement of 29%. In the production of domestic appliances, anomaly detection during dryer drum production processes triggers predictions of malfunctioning, consequently eliminating costs and reducing maintenance costs significantly. Besides, anomaly detection in terms of real-time readings of humidity, gyroscopes, acceleration, and temperature enhances appropriate decisions regarding optimal aircraft maintenance planning, finance/resource allocation, and faster generation of spare parts. Furthermore, anomaly detection in the steel industry on the vibrations, tachometers, and current sensor leads to a maximized equipment lifetime and reduced downtimes due to the prior timely preparation of maintenance processes. Therefore, predictive maintenance is associated with numerous advantages contributing to organizational efficiency and performance.

However, despite the main advantages of predictive maintenance technologies, many barriers hinder organizations from implementing them. For example, Golightly et al. (2018) demonstrate that the adoption of predictive maintenance technologies can be problematic due to human-related issues such as inadequate knowledge of interpreting data, large data sets, and ineffective decision-making in various roles. Equally, organizational challenges often exist in accommodating and implementing change, hindering the operational strategies' abilities to utilize advanced data-driven analysis tools. On the other hand, Carnero and Gomez (2017) classify the barriers to implementing sustainable predictive maintenance practices as financial obstacles, firm/organizational obstacles, data source-related limitations, and difficulties in optimizing maintenance strategies. For instance, since implementing advanced maintenance practices require information extraction, sensor installations, and preparing maintenance activities, many profit-minded organizations consider these activities as additional financial expenses and burden. Furthermore, while large companies are unwilling to invest in predictive maintenance technologies, many small and medium-sized industries lack adequate technological access. These barriers hinder the adoption and implementation of predictive maintenance technologies in many organizations worldwide.

1.2 Problem Statement and Research Justification

Despite the many advantages of predictive maintenance technologies and practices, few organizations have implemented them. According to Golightly et al. (2018), human technical deficiencies in interpreting large data sets and making effective decisions in various roles, financial and organizational obstacles, data source limitations, and challenges in optimizing predictive maintenance technologies, among other barriers, hinder many organizations' willingness and abilities to adopt and implement these technologies and practices. As such, there is a need to explore in depth the factors influencing the adoption and implementation of predictive maintenance technologies in organizations. Furthermore, the insignificant adoption of predictive maintenance technologies/practices, especially among the major organizations in the manufacturing sector, demonstrates the lack of understanding of their benefits, resulting in poor performance and productivity.

1.3 Research Questions

As a result, this study aims to answer the following research questions:

- What factors influence the adoption and implementation of predictive maintenance technologies in organizations?
- How do the factors influencing predictive maintenance technology adoption affect organizational performance?

1.4 Research objectives

The specific objectives of this study include the following:

- To determine the important variables influencing the adoption and use of PdM technology in businesses.
- To critically explore how these factors affect how well an organization performs.

1.5 Motivation of the research

While there have been a significant number of studies performed on the implementation of PdM in developed nations, there has only been a small amount of studies carried out on the Middle East region, especially in the United Arab Emirates (UAE), addressing PdM systems. In nations located in the Middle East, the issue of interest around the implementation of PdM systems is becoming an increasingly relevant one. The use of technological solutions and PdM systems has been a key factor in the growth of the economy in the UAE. Even though technology adoption theories have been well documented in academic literature, their application has generally been restricted to countries that are already considered developed. In addition, there has not been a lot of study done in the UAE on the factors that determine whether people accept and use PdM systems. The current investigation aims to fill up this gap in the existing body of research. The primary objective of this thesis will be to perform an in-depth examination of the myriad of elements, including political, cultural, social, technical, and personal considerations, that impact the implementation of PdM systems in the UAE. The purpose of the current research is to investigate, from the vantage point of organizational people, the potential repercussions that may result from the implementation of PdM systems. The purpose of this research is to investigate the impact that demographic characteristics have on the application and adoption of PdM systems. In addition to this, the researcher intends to investigate the projected economic and social benefits that come because of the implementation of such systems.

1.6 Significance of the study

The findings of this research study offer significant contributions to the cement manufacturing sector by providing insights that can aid in the development of effective interventions aimed at improving the adoption of data driven PdM techniques in their operations while maintaining cost-effectiveness. The implementation of the PdM technique in equipment maintenance operations is of paramount importance for cement manufacturing companies. This approach enables them to leverage the associated benefits and consequently improve their competitive standing.

The results of the study provide those in positions of authority a full grasp of the elements that impact the implementation of PdM in manufacturing companies. This crucial information may be used to guide the creation of policies as well as actions that are targeted at boosting the adoption of new technologies among producers. The Ministry of Information, Communications and Technology is credited as being the driving factor for the development of the Distributed Ledger and Artificial Intelligence Taskforce. The Ministry of Information, Communications, and Technology has initiated the establishment of a task group with the purpose of formulating an all-encompassing strategy for the incorporation of technologies related to the Fourth Industrial Revolution into the infrastructure of the country. It is projected that the use of these emerging technologies would have the effect of revolutionizing the manufacturing sector, consequently increasing the competitive advantage of the country in the market. This idea is best shown by the technique known as data-driven predictive maintenance

(PdM for short). The purpose of this research is to advise government agencies and relevant ministries on how to best execute policy changes and frameworks that would make it more appealing for manufacturers to make investments. Both the study approach and the findings have a relevant value for other researchers, educators, and students since they add to the present knowledge of this issue and provide a solid foundation for future inquiries into the area of new technologies. In addition, it is hoped that the results of the study would act as a catalyst for more research to be conducted in this very important field.

1.7 Definition of terms

1.7.1 Predictive maintenance

PdM involves the use of a forecast generated from repeated assessments or known attributes and appraisal of critical parameters to execute maintenance on equipment or parts that are experiencing degradation. Maintenance operations, such as repairs and replacements, are conducted based on an analysis of the present and future conditions of the physical assets, which may be measured, estimated, or calculated (Fritsch, 2011).

1.7.2 Adoption

The optimal utilization of technological advancements is crucial for any available endeavors.

1.8 Chapter summary

The present chapter presented the contextual framework of the research and the specific statement of the problem. Additionally, the research study provided an overview of its scope and delineated the research inquiries employed to investigate the determinants that exert a substantial impact on the implementation of predictive maintenance in the manufacturing sector. The definitions of various terminologies have been provided. Chapter two presents a thorough review of the literature pertaining to the factors that impact the adoption of predictive maintenance within the manufacturing industry of the UAE. Chapter three presents a comprehensive methodology employed during this research study. The fourth chapter of the study presented the research findings and provided an interpretation of the data that was collected. Chapter five provided an analysis and discussion of the findings, ultimately leading to the formulation of conclusions and recommendations for future research.

Chapter 2 Literature Review

2.1 Introduction

This chapter offers a thorough examination of the literature pertaining to the determinants that influence the implementation of intelligent or data-oriented predictive maintenance within manufacturing firms situated in the UAE. This review is grounded on the research of prior researchers who have explored this area of study. As per the argument presented, a literature review presents the researcher with a theoretical examination, an empirical inquiry, and a conceptual structure to guide their deliberations towards the exact essence of the topic being explored. The main aim of conducting a literature review is to explore the existing and readily available knowledge that has been analyzed by various scholars. The text presents a collection of opinions, attributes, research findings, and corresponding conclusions derived from prior research conducted by various individuals and institutions. The upcoming chapter shall provide an exposition of the theoretical literature, empirical studies, and conceptual framework. The formulation of the research question provides the fundamental framework for the examination of the various factors included in the study. The review was structured into distinct sub-sections that centered on the various factors that impact the adoption and implementation of PdM technologies.

2.2 Theoretical literature review

2.2.1 Innovation Diffusion Theory

The Innovation Diffusion Theory (IDT), which was first proposed by Albert Bandura, has been extensively employed to ascertain the determinants that impact the acceptance of diverse computer technologies and information technology (IT) practices (Alsyouf, 2007). The respective theory comprises the assimilation of ubiquitous Information Technology (IT), Electronic Data Interchange (EDI), web service standards, and the modalities of IT dissemination. Furthermore, scholars have utilized the theory to investigate the correlation between the adoption of information technology and the competitive advantage of companies in developed and developing countries. According to the diffusion of innovation theory proposed by Elliott (1992), innovations are disseminated through specific channels within a social system over time. Individuals within this system are believed to possess varying degrees of willingness to adopt innovations. As a result, the adoption of an innovation is typically distributed in a normal curve over time, with different categories of adopters including innovators, early adopters, early majority, late majority, and laggards (Cho et al., 2012). The individuals who are the earliest to adopt an innovation are commonly referred to as innovators. Individuals categorized as early adopters are the second most rapid group to adopt an innovation. These individuals exhibit the most significant level of opinion leadership compared to the other categories of adopters. Individuals in the Early Majority category tend to adopt an innovation after a certain amount of time has elapsed. The duration of adoption during this phase is notably longer than that of the innovators and early adopters. Individuals belonging to the Late Majority segment tend to adopt an innovation after the average member of society (Compare et al., 2019). These individuals exhibit a marked tendency towards skepticism when encountering a novel innovation. Individuals classified as laggards tend to be the final group to embrace innovation. Individuals in this category exhibit minimal to negligible levels of opinion leadership, in contrast to certain other categories.

2.2.2 Contingency Theory

The contingency theory posits that the optimal design of a PdM technology should be characterized by flexibility, considering the prevailing organizational structure and environment, to enhance the adoption and implementation of predictive maintenance technologies within organizations. The adaptation of PdM technologies to specific decision-making processes is necessary. Stated differently, developing PdM technologies within an adaptable framework is necessary. The accounting literature's initial paper that concentrated on the contingency perspective of PdM technologies was "A Contingency Framework for the Design of Predictive Maintenance Technologies." The present article has established the fundamental structure for the analysis of PdM technologies, considering a contingency viewpoint. According to the findings of Cho et al. (2012), successful organizations tend to develop PdM as a response to environmental uncertainty. One of the primary discoveries in this research was that decision-makers tend to pursue external, nonfinancial, and ex-ante information in conjunction with internal, financial, and ex-post information when they perceive a higher degree of environmental uncertainty (Davis, 1989). Despite being the subject of extensive research over the past two decades, contingency theory has received comparatively scant attention concerning its impact on PdM technologies.

2.2.3 Decomposed Theory of Planned Behavior

The Decomposed Theory of Planned Behaviour (DTPB) was developed by integrating the Technology Acceptance Model (TAM) proposed by Tao et al. (2020) and the Theory of Planned Behaviour (TPB) introduced. This theory aims to enhance comprehension of behavioral intention by focusing on the factors that are expected to influence the utilization of systems. TAM is a theoretical framework within information systems that depicts how users adopt and utilize a given technology. The presented model posits that users' adoption of a novel technology is influenced by various factors: Perceived Usefulness (PU) and Perceived Ease-Of-Use (PEOU). According to Davis (1989), an individual's attitude is significantly influenced by PEOU and PU through two primary mechanisms, such as self-efficacy and instrumentality. The DTPB model posits that an individual's attitude toward technology can be characterized by three distinct dimensions: relative advantage, complexity, and compatibility. According to Davis (1989), relative advantage pertains to the extent to which an innovation offers advantages that surpass those of other options. The advantages that may be derived from a particular course of action could encompass economic gains, improved public perception, increased ease of use, and heightened levels of contentment.

Within the framework of this investigation, it can be posited that computerized accounting systems represent an innovative approach that confers certain benefits over their manual counterparts [42]. Utilizing a computerized system results in increased efficiency, accelerated processing times, and reduced probability of errors. According to Rogers (2010), the capacity of innovation to conform to the adopter's pre-existing values, past experiences, and present requirements is referred to as compatibility. Present requirements, such as the expeditious processing of customer revenues, may impact the inclination of SMEs to embrace computerized accounting systems. Furthermore, the alignment between the cost of the system and the available resources is consistent with the current values (Duffy, 2012). Therefore, the adoption of the system may be influenced by the cost, given the available resources and competing needs of the firm.

2.2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model was formulated by Venkatesh et al. (2003) and combined theories and models related to technology acceptance and adoption. The UTAUT model is a theoretical framework that predicts individual employees' behavior regarding technology usage, drawing upon established technology adoption theories. The model integrates key components of theories and models about the acceptance of technology by users, as evaluated through the fundamental determinants of behavioral intention and user experience. The model developed and validated by Venkatesh et al. (2003) incorporates various constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions, which are considered key determinants of user behavioral intention and usage of information technology. The UTAUT model has been subject to criticism due to its limited applicability and low generalizability. The rationale is that the model, as mentioned above, underwent testing solely within the confines of organizational and academic settings, as per the research conducted by Oliveira et al. (2016). As a result, the UTAUT model possesses a greater degree of comprehensiveness compared to alternative technology adoption models. Adopting technology within power-driven organizations can be subject to the influence of power dynamics (Carnero & Gomez, 2017).

Moreover, certain occurrences prompt technology implementation, rendering it an imperative measure for survival in the fiercely competitive corporate landscape. Therefore, the UTAUT model must comprehensively elucidate the factors influencing an individual's decision to adopt a novel technology (Oliveira et al., 2016). A further constraint of the model pertains to its failure to establish a correlation between perceived advantages and the actions that may ensue from implementing technology.

2.2.5 Technology Acceptance Model (TAM)

TAM, an acronym for Technology Acceptance Model, was formulated by Davis (1989) as an extension of the TRA. Its primary focus is on forecasting the adoption of an information system. According to Davis (1989), the model offers a theoretical justification and is stingy in explaining user behavior across various technologies by elucidating the determinants of technology acceptance. According to TAM, adopting an information system is contingent upon two key determinants: perceived usefulness and ease of use. Perceived usefulness pertains to an individual's belief that utilizing a system will enhance their overall performance (Davis, 1989). Perceived ease of use pertains to an individual's perception of the level of exertion necessary to operate a given system. The enhancement of an individual's performance in an instrumental manner can be attributed to the perception of ease of use. Davis (1989) proposed a model highlighting the stronger association between perceived usefulness and the intention to use an information system compared to perceived ease of use. This observation is noteworthy. Per the model presented, it is anticipated that the primary determinant impacting most users is the perceived utility of a given tool. According to Hu et al. (1999), there may be better solutions than TAM for all technological acceptance issues, which may have certain limitations. Hu et al. (1999) assert that TAM fails to account for contextual factors such as cultural nuances, gender differences, and variations in information system types. According to Duffy's (2012) assertion, TAM constraints arise from its foundation on a research-oriented rather than a user-oriented perspective. Hence, the model's primary objective was not to enhance the pace of technology adoption but rather to identify factors that may impact technology acceptance. The theory acknowledges perceived ease of use and usefulness as fundamental elements in fostering the intention to adopt the technology. However, it fails to account for the potential effects of external factors, such as government or political influence. Political factors partially influence the accessibility of technology, and individuals are constrained to utilizing only the technology that is made available to them. The implementation of technology may be impeded by governmental regulations, despite the presence of behavioral intention (Oliveira et al., 2016). Therefore, TAM must still integrate this aspect into its theoretical framework.

2.2.6 Diffusion of Innovations Theory (DOI)

The DOI theory, which was formulated by Rogers in 1962, is one of the most longstanding social science theories (Rogers, 2010). The objective of this study is to elucidate the process by which an idea or product gradually receives popularity and spreads within a particular society or social framework. The outcome of this ultimate allocation is that individuals operating within the confines of a societal structure embrace a novel concept or conduct of a product. The term adoption refers to the act of an individual engaging in an alternative course of action from their prior behavior. For diffusion to occur, it is crucial that the individual perceives the adoption of a particular idea, behavior, or innovative product in a positive light (Cho et al., 2012). The process of adopting a novel idea, product, or behavior, commonly referred to as innovation, is not a synchronous phenomenon within a social system (Kaminski, 2011). Rather, it is a gradual process whereby certain individuals are more predisposed than others to adopt the innovation. The study conducted by the researchers revealed that individuals who exhibit early adoption of an innovation possess distinct traits in comparison to those who adopt it at a later stage. In the context of promoting innovation to a specific demographic, it is crucial to comprehend the distinct characteristics of the respective demographic and how they may facilitate or impede the assimilation of innovative practices. Zhang and Nuttall (2011) suggest that diverse approaches can be employed to appeal to the different adopter segments during the facilitation of innovation. The adopters can be classified into various categories.

Innovators are individuals who exhibit a propensity for being early adopters of novel ideas or technologies. Individuals who are innovative tend to exhibit a willingness to take risks and embrace novel concepts. Individuals exhibit a high degree of willingness to engage in risk-taking behavior and demonstrate enthusiasm toward the generation of novel concepts (Tao et al., 2020). There is a minimal need for intervention to draw the attention of this demographic.

Individuals who are among the first to adopt a new product or technology are commonly referred to as early adopters. These individuals are often considered opinion leaders, as their adoption behavior can influence the adoption behavior of others. Individuals who are quick to adopt new ideas tend to take on leadership positions and actively seek out relevant opportunities to bring about change. The individuals in question have demonstrated a cognizance of the necessity for modification and are, therefore, amenable to the concept of embracing novel concepts (Palazzeschi et al., 2018). Nonetheless, individuals require persuasive information to alter their stance, and they insist on empirical proof of the efficacy of innovation prior to embracing it. According to Ozer (2000), effective methods for engaging this demographic involve the provision of pragmatic manuals and details regarding implementation protocols, as well as the presentation of success narratives and empirical data that demonstrate the efficacy of innovative approaches.

The late majority demographic exhibits a reluctance to embrace and incorporate an innovation into their lives once it has become widely adopted by most of the population. To appeal to the late majority, it is advisable to provide them with information regarding the experiences of previous adopters who have successfully implemented an innovation.

Laggards are individuals who tend to adhere to traditional practices and exhibit a strong inclination toward conservatism in their thought processes (Sony & Naik, 2018). Individuals who are classified as laggards tend to exhibit a high degree of skepticism toward any proposed changes and, therefore, require a concerted effort to be convinced and brought on board with the proposed changes. The methods employed to appeal to this demographic encompass statistical data, fear-based tactics, and social influence exerted by adopters belonging to different groups.

The research conducted by DOI has resulted in the recognition of innovation characteristics that seemingly impact the spread of innovation at the individual level. These attributes include relative advantage, compatibility, complexity, trialability, and observability, as outlined by Rogers (2010). The phenomenon of DOI has been extensively researched across various disciplines, with a significant number of scholarly papers exceeding 4,000 in count. Notably, most of these papers were produced subsequent to the development of Rogers' systematic theory. It is worth mentioning that a few modifications have been implemented to the theory, which have gained widespread acceptance (Rogers, 2010). Despite variations in the application of the theory across different studies, the absence of coherence has resulted in a state of stagnation for the theory, rendering it challenging to consistently apply to novel problems. Research has conducted meta-analysis of 95 studies that utilized DOI theory to predict the rate of adoption outcome (van de Kerkhof, 2020). Among the surveyed studies, 43 focused on the concept of relative advantage, 27 examined compatibilities, 16 delved into complexity, and 13 explored trialability (Jin et al., 2016). Research has indicated that most studies, specifically 67%, have discovered statistically significant evidence in favor of both relative advantage and compatibility. Additionally, complexity and trialability have received support from 56% and 67% of studies, respectively. It is noteworthy that Midgely did not acknowledge or give preference to the attribute of observability.

2.2.7 Technological Determinism Theory (TD)

The TD perspective pertains to the theoretical framework that posits technology as the driving force behind societal transformation. Technology is regarded as a significant historical milestone within the realm of social change. In the realm of economics, it is commonly referred to as a technology push theory as opposed to a demand-pull theory. According to Fritsch (2011), proponents of technological determinism argue that advancements in technology, communication tools or media, or technology as a whole, are responsible for bringing about substantial transformations in society. Furthermore, proponents of technological determinism categorize technology as either universal or particular. The user examines the implications of technology, specifically communication technologies, on society across historical, contemporary, and prospective contexts. Technological determinists posit that the impact of technologies, such as computers, has been pervasive across various societal domains, encompassing institutional, social, international, and individual spheres. Moreover, it is widely acknowledged that technology plays a significant role in shaping social and cultural diversities, while human factors and social arrangements are deemed to be of secondary importance (Navas et al., 2020).

Karl Marx is widely regarded as a proponent of technological determinism, as he expounded on the profound and immediate influence of technology on society, despite some advocates contending otherwise. Conversely, several non-Marxist scholars have recorded the significance of technological determinism. TD is commonly associated with futurist analysts who describe it as a microelectronic revolution. As per Evans (1979), the computer is believed to be a revolutionary technology that has the potential to bring about significant transformations in societies worldwide, across all levels. TD has primarily concentrated on elucidating the influence of technology on society, culture, and social institutions, among other areas. While acknowledging the advantages that technology offers to society, the focus on the social consequences of technology and its impact on society and human interaction may offer a restricted comprehension of the reasons behind individuals' adoption of a particular technology (Oliveira et al., 2016). The present study incorporates a model that amalgamates the social and economic advantages that technology can offer to an individual or an organization.

2.3 Empirical literature review

2.3.1 User Perception

Innovative organizations may opt out of utilizing a computerized accounting system if they perceive it to be intricate in its operation. Oliveira et al. (2016) posited that the need for more skills in the workforce impacts the utilization of computerized systems. Consequently, organizations must ascertain the computerized system proficiency of their employees, as such knowledge and prior experiences may significantly impact the organization's decision-making process about the adoption of PdM technologies. Moreover, it is improbable that managers within an organization would only embrace advanced technologies with a prior acquaintance with the research conducted by Read (1996). Prior research has demonstrated a positive correlation between an organization's perceived benefits and the likelihood of adopting technology-based innovations, such as implementing a computerized accounting system. The primary impetus behind implementing PdM technologies is typically the expected advantages these technologies will yield for the organization (Premkumar & Roberts, 1999). Research has been conducted on multiple studies demonstrating PdM technologies' potential benefits for enhancing an organization's competitiveness. According to a study conducted by the OECD in 2004, the implementation of PdM technologies can enhance information and knowledge management within a company and improve the efficiency and dependability of transactions. Davis (1989) highlights that adopting PdM technologies within an organization can decrease expenses and enhance productivity, thereby rendering cost-effectiveness a compelling incentive for adopting such technologies. PdM technologies enhance efficiency by enabling cost-effective and expeditious communication, fostering improved relationships with customers and suppliers, facilitating more effective and efficient marketing, product, and service development, and providing enhanced access to information and training. Despite the numerous advantages of implementing PdM technologies, several organizations still need to leverage these technologies. Davis (1989) posits that technology's perceived ease of use and usefulness significantly impact an individual's attitude toward its acceptability and usage. Additional factors to be considered include the determination to implement modifications, the utilization of computerized systems, and the advantages that such systems can offer the organization.

2.3.2 Economic benefits

The primary objective of a business organization is to generate profits and enhance shareholder value, thus making economic advantages a crucial incentive for the adoption of novel technological innovations. Algabroun (2020) asserts that manufacturers operating in a dynamic and challenging environment strive to adopt new technologies such as PdM, which offer a relative advantage over classical approaches, to enhance their performance and secure their market share. This underscores the importance of maintenance in improving the performance and profitability of the production process. According to Haarman et al. (2018), integrating PdM technologies and big data analytics can generate significant value for manufacturing companies. The significance of the role of this type of technology in the manufacturing sector is experiencing a rapid increase, as per Ye's (2018) findings. The empirical testing of the adoption of PdM compared to other approaches was conducted in a case study in Sweden. The results of the study indicated that PdM directly impacted the quality, operation efficiency, and effectiveness of the manufacturing process. This impact, in turn, influenced the productivity and profitability of the process (Alsyouf, 2007).

The manufacturing industry in Belgium has expressed anticipation for implementing positioning maintenance through PdM to provide value to the business, as evidenced by a recent study. According to Patidar et al. (2017), a survey was conducted in the manufacturing industry of Belgium, where 46 participants were involved. The study revealed that 71% of the respondents believed that PdM could serve as a tool for improving the organization's competitive advantage. This finding has increased attention to the maintenance function, particularly in the current business climate. According to Ye's (2018) research conducted by IoT Analytics, a significant proportion of respondents (79%) regarded PdM adoption as a highly important IoT data analytics application that should be implemented in the manufacturing industry within the next one to three years. It has been noted that IoT Analytics is a prominent worldwide provider of market insights and strategic business intelligence for the domains of the Internet of Things (IoT), Artificial Intelligence (AI), Cloud, Edge computing, and Industry 4.0 (Thomas, 2018). In addition, the organization extends its assistance to enterprises in their digital transformation endeavors (Ramdani et al., 2013). According to the 'Predictive Maintenance- Market Report 2017-2022' by IoT Analytics, the market revenue for PdM was projected to attain $10.96 billion by 2022, with a compound annual growth rate of 39 percent in a rapidly expanding market (Oliveira et al., 2016).

It should be emphasized that although PdM can anticipate potential failures at an earlier stage, thereby conferring a comparative edge over other maintenance methodologies such as preventive maintenance, it necessitates a greater degree of the initial investment in capital expenditure and expertise, which has been identified as a hindrance to its widespread adoption (Lee et al., 2019). The assertion is supported by Algabroun’s (2020) empirical study, which underscores that adopting PdM is initially technologically demanding and necessitates a significant investment in maintenance, which can be costly. Nevertheless, companies can recover economic advantages over an extended period while maintaining sustainability (Williams et al., 2017). Lee et al. (2019) argue that the reduction of equipment risk concern significantly contributes to adopting the technology, particularly for high-value assets that have a major impact on product loss and cost of repair in the event of failure. Thomas (2018) reported that the implementation of PdM techniques had demonstrated a return on investment of 10:1. Thomas (2018) reported on a PdM adoption project conducted in the United States, which yielded a revenue increase of $17.22 million within the first two years of implementation, at an investment cost of $1.35 million. A case study conducted at a paper mill in Sweden revealed that the adoption of PdM resulted in an average annual cost increase of $45,500. According to Thomas (2018), the adoption of PdM showed a strong positive correlation to an average of $358,000 in additional annual profitability, with realized savings amounting to $3 million. According to Compare et al. (2019), manufacturing firms implementing PdM can experience additional economic advantages in managing equipment component spares in their warehouses. The utilization of remaining useful life (RUL) information by firms to establish a just-in-time logistics support system for a given part or component has been observed to reduce stored spares. This, in turn, has a positive impact on the company's net working capital and has been identified as a significant factor influencing the level of adoption.

2.3.3 Cost reduction

The integration of digital capabilities into new technologies, coupled with the existing market pressures to minimize expenses, has prompted manufacturers to shift their focus from reactive maintenance to data driven PdM per Ulring's (2020) findings. According to Jin et al. (2016), preventive maintenance has the potential to increase expenses for manufacturing firms significantly. As a result, there is a growing trend toward adopting a more efficient approach to predictive maintenance, particularly by implementing a just-in-time maintenance strategy. Certain scholars have classified maintenance as a function that generates profit, potentially due to its cost implications in manufacturing and its crucial role in achieving organizational goals (Alsyouf, 2007).

According to Patidar et al. (2017), the estimated maintenance costs for manufacturing are 6% of the company's turnover, equivalent to sales. However, this percentage can fluctuate between 0.5% to 25% depending on various factors, such as the quality of management and other specific circumstances unique to the firm. Furthermore, according to estimates, a significant proportion of the maintenance costs (30%) are deemed unnecessary due to inadequate planning or suboptimal execution of maintenance tasks (Thomas, 2018). This factor has been observed to impact the adoption rate of the PdM approach, despite its relative advantage in enabling just-in-time maintenance focus (Patidar et al., 2017). Research has indicated that the implementation of PdM, as opposed to corrective or preventive maintenance, can yield various beneficial outcomes across multiple domains. These include decreased overall maintenance expenses, decreased occurrences of defects and reworks, decreased instances of breakdowns or downtime, and decreased inventory levels (Thomas, 2018). According to van De Kerkhof's (2020) empirical research, implementing PdM has demonstrated its cost-effectiveness as a maintenance approach for assets prone to frequent failures and resulting in significant expenses when failing unexpectedly. According to Lee et al. (2019), it is agreed that the implementation of PdM can decrease maintenance expenses by means of component replacement, thereby minimizing or preventing the potential loss of equipment downtime during the given time frame. According to Thomas (2018), the expenses associated with reactive or corrective maintenance, such as parts and labor costs, are considerable and, therefore, deemed not financially viable, particularly in a competitive setting.

In contrast, it has been observed that PdM entails comparatively reduced maintenance labor and moderate parts expenses, while also yielding substantial cost savings. Adopting PdM by most manufacturing entities can reduce maintenance expenditure by as much as 30 percent compared to alternative methodologies. Algabroun (2020) conducted an empirical study that supports the notion that manufacturing companies can achieve cost-effectiveness by adopting new technologies such as PdM. The study suggests that the implementation of PdM can result in up to 20% savings due to reduced production losses resulting from fewer breakdowns and improved product quality. This approach offers a relative advantage over traditional maintenance methods. According to van De Kerkhof's (2020) research conducted in the manufacturing industry, it was discovered that cost savings ranged from 10-50%.

As per the findings of Haarman et al. (2018), the implementation of PdM can result in a 12% reduction in operational costs related to total production, a 20% increase in the lifespan of aging assets, and a 14% decrease in risks associated with health, safety, and environmental concerns. These results were obtained from a market survey report conducted in 2018. According to a study conducted by International Business Machines Corporation (IBM), a multinational technology corporation based in the United States, the implementation of their PdM services, namely the 'IBM Watson IoT platform' and 'IBM Cloud Functions,' resulted in the optimization of equipment maintenance and reduction of energy costs and wastage in two Israeli companies (Ulring, 2020). The study's findings indicate that the initial organization managed to curtail energy usage by approximately 25 percent, resulting in an annual cost savings of $170,000. The second enterprise achieved commendable outcomes by enhancing its compressed air system's monitoring, control, and optimization. As a result, the company managed to curtail its energy consumption by 30 percent, resulting in an annual saving of approximately $70,000. Based on research conducted by IBM in 2019, it has been found that industrial plants have the potential to achieve up to a 50% reduction in energy consumption through the implementation of PdM (Ulring, 2020). This finding indicates a strong and positive correlation between PdM adoption and energy savings.

2.3.4 Job effectiveness

The conventional understanding of the function of the maintenance department is to address and repair malfunctioning equipment or objects. Adopting a limited perspective has resulted in maintenance activities being restricted to reactive tasks such as repair actions or item replacement, consistent with other methodologies such as preventive and reactive maintenance. Golightly et al. (2018) conducted a study that revealed that certain manufacturing firms are motivated to adopt PdM to attain accurate maintenance scheduling. This approach offers two-fold benefits: firstly, it enables the identification of equipment degradation before actual failure, and secondly, it allows for maintenance planning and renewals to be responsive to the actual state of the equipment rather than being dictated by a fixed schedule. As such, this approach offers a relative advantage compared to current practices.

Furthermore, the study revealed that adequate preparation for repairs and professional execution of work resulted in enhanced job effectiveness among maintenance workers. van De Kerkhof (2020) posits that adopting PdM facilitates the acquisition of real-time condition monitoring data, which supports prompt equipment management decision-making. This renders PdM comparatively advantageous in comparison to other maintenance strategies.

Integrating data and analytics within the framework of PdM is causing a significant shift in the responsibilities of maintenance departments. Using sensors placed on equipment enables the continuous monitoring of equipment health, facilitating proactive measures and optimizing maintenance workforce utilization (Carnero & Gomez, 2017). This approach has been observed to substantially impact the adoption of PdM, as reported by Navas et al. (2020). According to Ozer (2000), the responsibilities of technicians will not solely involve identifying particular malfunctions. Instead, they will utilize performance benchmarks that rely on data provided by sensors and monitored through algorithms. These benchmarks can accurately detect when a piece of equipment is operating outside of its typical parameters, thereby improving the efficiency of its work.

2.3.5 Effectiveness and efficiency

In the present-day business landscape, manufacturing enterprises must implement an appropriate maintenance strategy to oversee, administer, and enhance their equipment's utilization, efficiency, and productivity (in terms of output and labor). This is due to the dynamic and demanding nature of the business environment, as highlighted by Patidar et al. (2017). According to Jin et al. (2016), the development of a successful maintenance strategy for a manufacturing company requires engineering endeavors that maximize the correlation between equipment ownership and operating profits. This is achieved by striking a balance between the expenses incurred in maintenance and those resulting from equipment degradation, wear, and failures, ultimately leading to production losses. Implementing PdM in a manufacturing company typically involves an initial investment due to the increased need for technological preparedness. However, it has the potential to significantly reduce avoidable failures and costs, prolong the lifespan of equipment, and decrease product defects. As a result, it offers a comparative advantage over-reactive and preventive maintenance strategies (Jin et al., 2016). van De Kerkhof (2020) posits that adopting PdM can enhance equipment productivity by improving availability and identifying efficiency losses, prolonging equipment's useful life by repairing degradation early and postponing periodic replacements, and mitigating safety hazards by preventing failure or reducing its consequences. PdM involves utilizing data from condition monitoring to detect anomalies in manufacturing equipment deviations from typical operating conditions. PdM also involves diagnosing the abnormal state and predicting its future evolution up to failure. This approach is highly effective and has positively impacted the adoption rate of manufacturing firms, as evidenced by research conducted by Compare et al. (2019).

Prognostics and Health Management (PHM) is commonly used to describe the collection of detection, diagnostic, and prognostic tasks (Compare et al., 2019). According to Haarman et al. (2018), market report suggests that adopting PdM will likely result in a 9% increase in equipment uptime, leading to a corresponding increase in production time. This finding underscores the efficacy of PdM and is expected to impact its adoption positively. The adoption of PdM is influenced by its effectiveness and efficiency aspects, as evidenced by the expected increase in labor productivity, inventory reduction, output/production increase, reduction in customer rejections, and workplace incidents. This is supported by the works of Thomas (2018). According to Thomas (2018), the Environmental Protection Agency (EPA), which is responsible for environmental protection in the United States, has estimated that the implementation of PdM can result in a notable enhancement of equipment efficiency, ranging from 15 to 25 percent. This improvement in efficiency has the potential to impact the adoption rate of PdM among manufacturing firms significantly. Compared to other maintenance methodologies, one notable advantage of implementing PdM in the manufacturing industry is the enhancement of electrical efficiency in equipment. Thomas (2018) conducted an empirical investigation in the United States, which revealed that the annual cost of reactive maintenance for equipment such as fans was $24 per megawatt.

In contrast, preventive maintenance incurred a cost of $18 per megawatt. However, the adoption of PdM decreased cost to $12, indicating a noteworthy enhancement in electrical efficiency. Consequently, PdM is relatively advantageous from an efficiency perspective, demonstrating a positive correlation. The significance of this matter is amplified for the UAE, given that its power expenses are the most elevated in the area, as reported by the Energy and Petroleum Regulatory Authority (EPRA) and GlobalPetrolPrices.com in 2021 (NS Energy, 2020). Additionally, the cement manufacturing sector in the region is characterized by a high dependence on electrical energy, as noted by the European Cement Association in 2021.

The improvement has significantly influenced the adoption of PdM in product quality consistency, which is crucial for meeting customer expectations. According to Thomas (2018), before implementing the PdM project, the PdM case study reported quality losses of 9% concerning production volume. Additionally, the plant was operating at 57% of its installed capacity. The implementation of PdM resulted in a decrease in quality losses to 4 percent and an increase in operational efficiency to 94 percent of installed capacity. This indicates a positive correlation between the level of adoption and the observed outcomes (Thomas, 2018). The optimization of maintenance operations within a manufacturing organization is a crucial factor in achieving its goals within a competitive market. This aspect has been analyzed in PdM. Ye (2018) posits that implementing PdM enables companies to mitigate the negative impact of unplanned or unnecessary maintenance on production hours and reduce costs associated with spare parts and supplies.

Additionally, PdM facilitates the efficient allocation of human resources. According to Ye (2018), the adoption of IoT-enabled PdM is positively influenced by its ability to achieve over 20% of addressable costs and production and operational benefits. Research contends that a significant portion of the manufacturing industry's yearly maintenance budget is wasted due to inefficient and unnecessary maintenance practices (Algabroun, 2020). This aligns with the author's perspective. According to Vogl et al. (2019), the application of preventive maintenance in manufacturing firms is excessive, with up to 50% of the time being deemed unnecessary. The adoption of data driven PdM presents an opportunity for cost-efficiency and relative advantage (Li et al., 2019).

2.3.6 Technological factors

The adoption readiness of PdM for industrial equipment in manufacturing firms can be facilitated during the design phase by Original Equipment Manufacturers (OEMs), which can improve the necessary technological compatibility and has been observed to have a positive correlation with successful adoption. The study conducted by Ingemarsdotter et al. (2019) found that OEMs can enhance the adoption of PdM among firms by incorporating necessary sensors and hardware for obtaining accurate information about the equipment's state. This integration enables OEMs to remotely monitor their customers' products and provide PdM as a value proposition within a service-based model. However, it is not a widespread practice among most OEMs. Although there is a potential business opportunity to provide PdM as a service, OEMs face challenges in implementing it, which makes it challenging for manufacturing firms to adopt it due to the investment required for technology readiness (Ingemarsdotter et al., 2019).

The effectiveness of PdM is dependent on the extensive collection and analysis of data from various systems to facilitate prompt equipment decision-making. However, the adoption of PdM by organizations is hindered by a data integration challenge. The challenge of compatibility arises when various ICT systems with distinct formats are utilized to produce, collect, and process data. It has been observed that various systems have been implemented at different points in time, by diverse vendors, and for varying objectives, often without considering the need for inter-connectivity (Compare et al., 2019). The authors provide examples of pertinent information and communication technology (ICT) systems utilized in manufacturing companies, including the Computerized Maintenance Management System (CMMS), which serves as the foundation for traditional maintenance record-keeping methods and primarily enables the use of written explanations of equipment malfunctions and corresponding actions taken; the Condition Monitoring (CM) system, which directly observes asset component parameters; the Supervisory Control and Data Acquisition (SCADA) system, which oversees processes and equipment control; and the Enterprise Resource Planning (ERP) system, which manages business functions, among other systems.

Erol et al. (2017) conducted a study on technological compatibility and identified that the unsuitability of current IT infrastructure and technologies, as well as significant financial investment and costs, are the primary obstacles to implementing PdM in manufacturing organizations. Li et al. (2019) noted that the technical complexity of PdM, deficiencies in the development of Internet of Things (IoT), inadequate machine integration, and high costs are factors impeding the adoption of PdM by manufacturing firms.

Regarding the discussed topic, Loorpuu (2020) conducted a research study which concluded that the implementation of PdM solutions requires a robust and compatible backbone of operational and information technologies (IT/OT) or ICT infrastructure. The presence of a central data integration historian in firms enables access to all historical process and maintenance data from a single location, resulting in increased compatibility and ease of implementation. This attribute is positively correlated with the level of adoption of PdM. According to Loorpuu (2020), the process of adopting PdM is made seamless due to the centralization, which allows for the implementation of a 'plug and play' concept. This eliminates the need to extract data from numerous sources with varying data structures, which would otherwise result in a significant amount of additional work for maintenance personnel. The availability of historical failure and process data with a coherent structure was considered crucial for enhancing implementation efficiency, which in turn impacted the levels of adoption (Ye, 2018)>

Scholars have directed their attention toward the influence of heightened information security risks on the adoption of PdM, particularly considering the prevailing pattern of a growing quantity of embedded devices, including manufacturing machinery linked to IoT networks. IoT is responsible for generating real-time processes and exchanging large amounts of security-sensitive data through industrial devices and systems. This makes them vulnerable and an attractive target for cyber-attacks (Sadeghi et al., 2015). The vulnerability of IoT networks to cyber-attacks is attributed to their interoperability with multiple devices (Palazzeschi et al., 2018). Attacks on IoT systems are of utmost importance due to the potential for physical harm, cessation or interruption of production processes, and significant safety and economic losses resulting from security breaches. The intricate nature of such systems and the possible ramifications of cyber-attacks give rise to new hazards, which are inversely related to the implementation of PdM among manufacturing firms.

According to Sadeghi et al. (2015), it is imperative for manufacturing companies to ensure that their IoT systems are adequately optimized to meet the necessary functional specifications while simultaneously mitigating security and privacy risks. The implementation of strong information technology security measures, both internally and externally, is crucial for the long-term success of PdM and to increase its adoption rates, as noted by various scholars. Gebremichael et al. (2020) assert that the implementation of compatible security and privacy-ensuring mechanisms is crucial for ensuring safe and reliable operations. They argue that such measures are necessary to increase the success level of PdM implementation within an organization. According to Li et al. (2019), manufacturing firms that contemplate the implementation of PdM must possess suitable data encryption and protection mechanisms. In addition to the threat of cyber-attacks, the integration of advanced technologies in the internet within the context of PdM poses a significant industrial security risk. This is due to the system's susceptibility to unauthorized remote access, internal network access through unauthorized devices, unauthorized asset leaks, employee error, and intentional program leaks. These factors have a detrimental impact on the adoption of PdM (Zhang & Nuttall, 2011).

2.3.7 Organizational factors

The implementation of PdM extends beyond the domains of production and maintenance, and encompasses a wide range of organizational, sectoral, and societal aspects. The influence of PdM on the organizational strategy is of utmost importance. As per the findings of Sony and Naik (2018), the strategy must account for the projected modifications in the organization's relationship with (a) its surroundings; (b) its communities; (c) its value chains; (d) and individuals, apart from the technical aspects of implementation. Sony and Naik (2018) posit that the mentioned relationships are crucial factors in determining the organizational compatibility necessary for the adoption of PdM. According to van De Kerkhof's (2020) research, the implementation of PdM technologies in a company can present challenges, particularly when the technology is intricate, costly, incompatible, and clashes with established institutional logics. Therefore, it is crucial to ensure alignment with the organization to achieve successful adoption.

The compatibility between PdM and the organizational strategy has been extensively investigated by researchers. Scholars have identified the absence of a strategic planning mindset as an organizational factor that may impact the implementation of new information technologies and systems such as PdM. The lack of strategic knowledge among managers and practitioners in adopting relevant strategies may result in inadequate strategic vision for digital projects, insufficient planning for technical and business development, and improper implementation plans. This may ultimately have a negative correlation with the level of adoption in manufacturing firms (Bokrantz et al., 2017).

According to Algabroun’s (2020) study, many adopting firms or those with the intention to adopt face a limited connection between their maintenance strategy and organizational strategy. This lack of connection often results in a disconnect, which can negatively impact the level of adoption of PdM. The authors observed that a significant number of manufacturing firms lack a structured maintenance strategy, indicating a tendency toward implementing short-term measures aimed at minimizing direct maintenance expenses. According to Golightly et al. (2018), it is imperative for management to ensure that the implementation of PdM aligns with the maintenance strategy of the department or organization in order to achieve successful outcomes. Algabroun (2020) argues that firms that fail to seize strategic maintenance initiatives may forego the chance to benefit from emerging technologies, which could ultimately enhance the organization's performance and sustainability.

Like other significant organizational changes, the introduction of PdM in a manufacturing company necessitates a clear vision to guide the implementation of the new business approach. However, many manufacturing firms are encountering difficulties in this area, which is adversely affecting the adoption rate of PdM, as evidenced by a study conducted in Austria (Loorpuu, 2020). According to Loorpuu's (2020) research on the adoption of PdM, it was found that a clear maintenance vision and a comprehensive understanding of how PdM strategy aligns with the organization's existing strategy, processes, and systems are crucial factors that enhance compatibility and are necessary for successful PdM adoption.

The successful adoption of PdM has been found to have a positive correlation with employee adaptability to novel technologies, which is also influenced by the organizational strategy. Sony and Naik (2018) posit that an organization that invests in employee training is more likely to enhance its adaptability and improve compatibility with the new skill requirements of PdM. The mentioned assertion is corroborated by Loorpuu's (2020) research, which indicates that companies that exhibit greater levels of innovation and are early adopters of emerging technologies are more inclined to adopt PdM. This is due to a heightened motivation, employee flexibility, and willingness to adapt to evolving technological landscapes, which in turn reduces internal resistance.

The implementation of PdM in a manufacturing company is contingent upon the internal context and organizational structure, despite being propelled by sophisticated technologies such as artificial intelligence, big data analytics, and IoT (Patidar et al., 2017). The significance of this matter lies in the fact that addressing issues and obstacles that arise during the implementation phase necessitates more than just a focus on technological or engineering advancements. It also hinges on the effective adoption and management of the respective technology within organizational contexts. Golightly et al. (2018) assert that the adoption of PdM is significantly influenced by the appropriate organizational culture. Therefore, it is imperative for top leadership to provide support for the delivery of the technology, as well as the modification of processes and practices within the organization to maximize the benefits of PdM implementation. The study conducted by Palazzeschi et al. (2018) revealed that the establishment of an organizational climate that fosters change, the cultivation of leaders who possess the necessary skills and behaviors conducive to change, and the adaptive acceptance of change are key factors that increase the probability of successful adoption of PdM within an organization. Furthermore, the authors posit that this viewpoint entails the necessity of effectively overseeing employees possessing novel skill sets to enhance adaptability, fortitude, and eagerness for the unknown, thereby encouraging their active participation in uncharted territories.

The correlation between the adoption of PdM and top management commitment is widely acknowledged as a crucial determinant of success. The provision of consistent support and dedication has been identified as a vital factor in facilitating the allocation of adequate resources towards the implementation of PdM. Additionally, it plays a crucial role in mitigating potential conflicts within the organization and addressing any resistance from end users (van de Kerkhof, 2020). According to Palazzeschi et al. (2018), researchers have identified specific leadership styles and strategic leaders that can improve overall organizational performance and reduce resistance to change. These factors can have a positive influence on the successful implementation of technological innovations such as PdM and facilitate effective transitions. The authors contend that the comprehensive management of human resources will play a pivotal role in the effective implementation of PdM within a manufacturing organization. Furthermore, they assert that top-level management serves as a catalyst for maintaining the new approach, particularly in response to the knowledge and competency obstacles that may arise.

Golightly et al. (2018) discovered that organizational factors, such as resource allocation in terms of time, personnel, and finances, significantly impacted the degree of PdM implementation. According to Wagner and Hellingrath (2019), PdM initiatives are predominantly instigated by business management, thereby constituting the primary project stakeholders. In addition to budgetary allocation, these stakeholders play a crucial role in delineating the project's scope, requirements, and expectations. Thus, it is imperative to have strong managerial support, as it is closely linked to the effective implementation of PdM initiatives. The statement aligns with the findings of Golightly et al.'s (2018) research, which emphasizes the crucial role of organizational leadership in facilitating the effective implementation and utilization of innovative technologies such as PdM.

The significance of ensuring successful adoption of technological innovations has been observed to be contingent upon the presence of organization-wide support and alignment.

Shafiee (2015) posits that the effective implementation of maintenance strategies, such as PdM, within an organization is directly associated with the level of support from stakeholders and the acceptance of personnel. The perspective is supported by Li et al. (2019), whose research on the integration of big data technologies in manufacturing factories revealed that inadequate collaboration and alignment among departments, particularly in cases where different departments or functions within the organization vie for resources or possess divergent objectives and conflicting interests, can result in misalignment that impedes the implementation of PdM initiatives.

The attainment of a shared comprehension of the rationale behind the implementation of PdM in a company is facilitated by a high degree of alignment among stakeholders. This, in turn, promotes improved collaboration toward a shared goal across all organizational levels, and is strongly correlated with the level of adoption (Gebremichael et al., 2020). According to Wagner and Hellingrath (2019), effective implementation in manufacturing firms requires significant emphasis on support and collaboration among diverse individuals, skills, and departments.

The literature emphasizes that the size of an enterprise influences adoption factors of technological advancements. According to Algabroun (2020), certain technological components required for predictive maintenance, such as hardware and software, may be excessively intricate for smaller enterprises, thereby impeding their ability to adopt such practices. The study revealed that large corporations, such as multinational companies, exhibit a greater propensity to implement initiatives, potentially attributable to their resource capacity and the synergistic impact of other departments, as well as central headquarters coordination.

2.3.8 Individual factors

The acceptance of the new technology by workers is essential to the successful implementation of any preventative maintenance approach, such as PdM, in a manufacturing company. According to the findings of a research conducted by Shaffie (2015), maintenance engineers prefer an approach to maintenance if it is simple to grasp and put into practice, and this factor impacts the ease with which they adopt PdM. The author suggests that because of this factor, managers need to generate a high degree of awareness among the team by discussing the characteristics of the new system and how it differs from the one that was used before to increase the level of compatibility. User resistance has also been identified as a factor that influences the level of PdM adoption in manufacturing companies (Vogl et al., 2019). This occurs when individuals are cautious about new technologies that they do not understand, and more importantly, when they feel that their knowledge and skills might become obsolete, which causes them to express concerns about their job security.

In their research, Wagner and Hellingrath (2019) noticed that the external project team responsible for implementing the PdM is often met with hesitation and misinformation from various individuals inside the company. This finding is connected to the user resistance part of the research. The authors contend that from the point of view of the company's equipment operator, PdM offers an unclear shift in the workflows of the organization. A portion of the concern relates to the possibility that the new technology would make their jobs more difficult or possibly render their employment obsolete. In addition, the maintenance department may adopt a defensive stance, which may make it more difficult for PdM to be accepted. PdM complicates the planning of maintenance operations as they perceive them in comparison to time-based maintenance, which has set maintenance periods (Read, 1996). Even when failures are known in advance, PdM makes the planning of maintenance activities more difficult. In situations in which a company's own project team is implementing a PdM solution, mistrust in the project may be prevalent due to a lack of internal competences in PdM.

According to the findings of Golighty et al. (2018)'s research, implementing organizations must make accommodations for the time needs of individual staff members to enhance the rate of successful adoption. The authors suggest that implementing a PdM solution would demand a degree of effort that is "above the day job" for the individual employees due to the amount of time that will be necessary for their consultation, training, and the actual execution of the project. Therefore, the authors suggest that extra workload should be addressed, and adequate resources should be allocated accordingly. Particularly since the primary objective of the remote condition monitoring and prognostic systems that PdM offers is to provide information, planning and decision support to people supporting equipment and equipment maintenance, the relation between users and technology and artifacts related to PdM adoption by manufacturing firms has been a matter of focus (Riggins & Wamba, 2015).

This is very important since PdM still needs human engagement in data analysis and the discussion of implications to the maintenance crew working on the shop floor to put the findings into action.

According to the findings of a research study conducted by Golighty et al. (2018), the level of adoption is positively correlated with getting the representation right, so that patterns in the data are clear, meaningful, and in a way that is compatible with the user performance needs. This is because data driven PdM requires the integration and presentation of information from multiple sources in a manner that supports decision making. In their respective studies, Vogl et al. (2019) underline the significance of straightforward and user-friendly information systems for industrial applications in the context of user decision support. The authors believe that the absence of user-friendly industrial applications of predictive maintenance and the fact that maintenance end users often lack the required data to drive decision making are contributing factors to the delayed adoption of PdM. The research study that was conducted by Golighty et al. (2018) emphasized the significance of striking a healthy balance between the hazards of simplifying, which conceals an excessive amount of the data, and the overloading of consumers with all types of raw data streams. It is necessary to demonstrate the nature of the data that underlies a choice by highlighting significant linkages in the data. This not only assures that consumers will trust the data, but it is also important.

Wagner and Hellingrath (2019), in their respective study, discuss the significance of including end users in a variety of decision-making processes so that the design of the PdM solution may be tailored to meet the requirements of the users. According to the authors' argument, the people of the production department, for example, as well as the equipment operator, supply extra supporting knowledge on the machine and the necessary processes based on their day-to-day interactions with the machine. They are the primary consumers of the PdM solution once it has been deployed, and as operators of the equipment, they should be involved in the design of the solution (especially during the data visualization phase). In addition, Golighty et al. (2018) discovered that during the development stage of a PdM solution in an organization, working closely with both operational (e.g., maintenance) and strategic (e.g., planning) staff to capture their ideas and embed them within the design solution was found to have a positive correlation with level of adoption, which in turn increased the likelihood of successful implementation. This was one of the most important findings.

2.3.9 Environmental factors

According to Golightly et al. (2018), government standards and regulatory organizations may be a possible obstacle to the adoption of PdM in a manufacturing company. This might be the case, for instance, in a scenario in which certification of PdM-related equipment with monitoring technologies is prevented. It is also possible to play the role of an enabler by providing support for digitization initiatives after they have been deployed and by fostering knowledge exchange within sectors. For instance, this may be accomplished by establishing centers of excellence that are able to record and distribute accumulated expertise. PdM can accomplish its goals because to the sharing of data and information amongst its many constituent parts (such as machines, sensors, people, and AI, among others). Without the establishment of proper norms and laws that define the character of the exchanges that take place between these components, this kind of cooperation is not going to be achievable. This may, in the near term, complicate the integration and communication among different aspects, consequently adversely associating with effective adoption (Shafiee, 2015).The establishment of such standards is currently a work in progress. For the effective deployment of PdM, legal concerns will also need to be taken into consideration. These concerns include, among other things, liability problems, data ownership, intellectual property, and safety and security (Bokrantz et al., 2017).

The technology market is an essential component of the implementation of PdM. According to Algabroun (2020), one of the most important enablers is the ongoing development of software and hardware, which has the effect of bringing costs down. Another essential enabler is the growth of new techniques and ideas, such as IoT, Internet of Service (IoS), and Cyber-Physical Systems (CPS). This is having a favorable connection in the adoption of PdM by manufacturing enterprises because the market delivers competitive options for the different implementation needs and is predicted to develop rapidly. According to the research carried out by Golightly et al. (2018), one of the factors that might affect the implementation of PdM is the connection that exists between manufacturing companies and the technology providers. The authors discovered that successful adoption of PdM was significantly correlated with instances in which suppliers worked closely with user organizations to ensure that the knowledge continues to be available to those organizations, and in which the user organizations, in turn, continued to remain aware of and maintain an ongoing relationship with their suppliers in order to remain updated not only on the solution performance, but also on PdM's future technological evolution.

In this context, Schmidt (2018) investigated the cross-organizational aspects in the supply chain, such as access to common knowledge across different organizations. According to the author, one of the most important factors that contributed to the successful deployment of PdM was a knowledge of the technical capabilities of the system as well as an acceptance of the fact that the PdM technology is reliant on third parties and that it is anticipated to stay operational throughout the lifetime of the system. In his research study, Loorpuu (2020) looked at the complexity of the supply chain, which he found to be far higher than what was anticipated at the beginning of the PdM implementation process. This was tied to both technical concerns as well as a "knowledge supply chain" of expertise that was often scattered across different companies and needed to be tapped into. The author suggested that the information contained within this supply chain must be both visible (the technology must be effectively described) and controlled (that is, it must be available on demand), and that this must have a positive correlation with the amount of successful adoption of PdM in manufacturing organizations. Despite the benefits that may be gained from collaborating across several organizations, manufacturing companies still need to take into consideration concerns around trust and intellectual property in order to successfully embrace PdM (Schmidt, 2018).

2.3.10 Complexity and adoption of Smart Predictive Maintenance

The concept of complexity, with respect to the adoption of novel technology, refers to the degree to which innovative technologies are perceived as difficult to comprehend and employ (Rogers, 2010). This construct exhibits a negative correlation with the adoption of innovation, such that if the technology is readily comprehensible within the organization and the necessary expertise is available, then implementation is likely to proceed smoothly and with ease, and conversely, if the technology is perceived as complex, then adoption may be impeded (Shamim et al., 2017).

2.3.11 Technical skills

The effective implementation of PdM in manufacturing firms necessitates the utilization of multiple sensors and sophisticated software for the purpose of prognosticating and diagnosing equipment failure modes. As per Shaffie's (2015) observations, the maintenance personnel must undergo comprehensive training to acquire proficiency in handling the relevant tools and techniques. The study conducted by Wagner and Hellingrath (2019) highlights the significance of the maintenance department's knowledge and engineering expertise as a crucial element in the effective implementation of PdM. Maintenance personnel possess a comprehensive comprehension of the machinery and are cognizant of previous malfunctions. Consequently, they can provide significant assistance in data analysis during implementation, as they can correlate identified irregularities in the data with their expertise. The significance of knowledge during the design, development, and operational stages of PdM was emphasized by Golightly and colleagues in their 2018 publication. The significance of both the particulars of PdM and a broader comprehension of ICT have been identified as critical determinants for the effective implementation of PdM initiatives in manufacturing enterprises. The successful implementation of adoption within a firm requires a robust digital infrastructure that encompasses both Information Technology (IT) and Operational Technology (OT). This, in turn, necessitates the acquisition of new organizational capabilities, which can be achieved through the recruitment of additional data analysis specialists (Riggins & Wamba, 2015).

Furthermore, Golighty et al. (2018) assert that the implementation of PdM may encounter significant obstacles stemming from human factors, including insufficient expertise and proficiency in data interpretation, particularly with respect to voluminous data sets, as well as the need to customize data and decision-making processes to suit diverse roles. In their study, Algabroun (2020) emphasize the significant challenges associated with managing extensive big data, including a lack of user-friendly systems and low competencies. These challenges may ultimately hinder the successful adoption of PdM by firms. According to

Schallehn et al. (2018), a survey conducted by Bain and Company found that manufacturing companies are impeded from adopting new Industry 4.0 technologies, such as PdM, at a quicker pace due to the complexity caused by a lack of expertise and established methods. Li et al. (2019) conducted a study that examined the issue of skillset requirements for consultants and data scientists in industrial big data projects such as PdM. The study found that the technical complexity of these projects necessitates the involvement of highly skilled data scientists and consultants with extensive skillsets. However, the scarcity of such professionals and their high demand negatively impacts the adoption level of these projects.

Bokrantz et al. (2017) concur that the adoption of a PdM approach in a manufacturing firm will introduce novel challenges to its workforce, necessitating the acquisition of advanced digital competencies. Moreover, it is asserted that organizations must prioritize adequate recruitment, training, and education to effectively utilize the competencies present within the organization. Maintenance personnel are required to acquire enhanced analytical, information and communication technology, social, business, adaptability, and technical competencies to effectively implement predictive maintenance. In 2015, IBM conducted a study on the delayed implementation of Industry 4.0 technologies, such as PdM. The research found that the complexity and insufficient expertise were major hindrances to the adoption rate (Talukder, 2011). According to Loorpuu's (2020) research, the absence of appropriate predictive maintenance (PdM) capabilities within an organization has been identified as a significant impediment to its adoption. This is due to the inadequate capacity to conduct extensive data analysis, reconfigure maintenance processes and strategies in accordance with PdM, and the need for skilled professionals to develop algorithms. Loorpuu (2020) posits that the adoption of a data driven PdM approach and higher maintenance maturity levels by manufacturing firms results in an increase in technical complexity. Consequently, this increase in technical complexity demands greater competences from the firms, which negatively affects adoption levels.

Researchers have explored the significance of knowledge and knowledge management within an organization, as well as its impact on the level of PdM adoption. This factor has been deemed important for various reasons (Xu et al., 2016). The implementation of PdM projects requires a significant amount of time and may involve organizational changes.

Therefore, it is crucial to ensure that knowledge is preserved in some manner from the implementing team. In projects that entail the participation of various vendors and partners, there exists a significant likelihood of critical knowledge and comprehension of the design rationale being forfeited upon the dissolution of the primary project team. Thirdly, it is imperative to possess an understanding of how to optimize the advantages derived from the analysis being produced. It is imperative to continuously capture and preserve various knowledge sources through an ongoing process. Failure to do so may result in a lack of comprehension regarding the application or support of PdM technology, ultimately leading to its rejection. This assertion is supported by instances where knowledge was not maintained, resulting in such negative outcomes. The authors acknowledge that effective management of the implementing team and partnerships with vendors, through training, handover, and relationship-building, increases the likelihood of successful long-term adoption (Sony & Naik, 2018).

According to Shamim et al. (2017), the adoption of PdM presents a certain degree of intricacy for organizations, which necessitates a team that is consistently engaged in innovation and learning, relying on the abilities of both the employees and the enterprise. Hence, the implementation of suitable managerial strategies can significantly contribute to the enhancement of dynamic capabilities, efficient learning, and a culture of innovation within the organization, ensuring the continuous adoption of PdM.

2.3.12 Communication

Loorpuu (2020) emphasized that inadequate communication and misinterpretations among stakeholders may result in unrealistic anticipations and unsuccessful PdM initiatives, as well as unproductive collaborations, particularly with technology vendors. According to Golightly et al. (2018), effective adoption can be facilitated through the implementation of reinforced and targeted communication strategies within the organization. As per the authors' perspective, it is imperative for the management to exhibit the significance of PdM solutions to the operational staff. The cost-effectiveness of PdM is a primary concern for top management, whereas operational staff prioritize its practical value and impact on their daily tasks. The practical applications of PdM technology, which can effectively minimize unplanned downtime, expedite diagnostic procedures, and optimize resource utilization, should be discussed with operational personnel to secure their support. Such discussions are crucial for achieving buy-in. Through the utilization of effective communication techniques and appropriate tools, it is possible to engage operational personnel and transform them into change agents. As such, they can effectively promote the adoption of PdM technology and generate support for its implementation.

The limited understanding of the entire PdM process can impede interdepartmental and cross-functional communication, which has been found to have an adverse impact on the successful implementation of PdM (Palazzeschi et al., 2018). Considering this aspect, it is imperative to formulate a comprehensive project plan and communicate the associated expectations to all stakeholders and departments involved, thereby fostering a heightened level of dedication towards the project.

2.3.13 Level of understanding

Despite the recognition of the substantial potential advantages of the associated business models arising from PdM, companies have encountered significant obstacles in advancing towards the formulation of a tailored corporate strategy for implementation, resulting in inadequate conceptualization of actionable domains. The study conducted by Ingemarsdotter et al. (2019) emphasizes the insufficient comprehension within the manufacturing sector, which results in increased complexity and hinders the implementation of data-driven predictive maintenance. The authors have identified a discrepancy between the current academic research focus and the practical challenges that companies encounter when implementing PdM. As a result, they have called for more research that is practice-oriented to gain a better understanding of the implementation challenges in practice, particularly those that extend beyond purely technological aspects.

According to Erol et al. (2017), four-year empirical study, two primary bottlenecks have been identified in the implementation of PdM in manufacturing companies. Two primary challenges hindering the operational execution of PdM are identified: firstly, the high level of abstraction associated with PdM, and secondly, the absence of clear guidance for the operational implementation of its concepts. The adoption of new information technologies and systems such as PdM can be influenced by a perceived complexity, leading to a lack of understanding (Wagner & Hellingrath, 2019). The deficiency of knowledge and comprehension of PdM and its related technologies can impede the appropriate implementation of PdM, which managers and practitioners of adopting organizations may encounter (Shafiee, 2015). Riggins and Wamba (2015) contended that the absence of comprehensive comprehension among managers regarding the multidisciplinary aspects necessary for the implementation of IoT and big data solutions impedes their capacity to formulate all-encompassing strategic plans during the execution of such innovative projects.

Schmidt (2018) has identified a deficiency in the systematic approach to the design and implementation of PdM systems. This is attributed to a lack of comprehensive comprehension by manufacturing firms, which has a negative correlation with the levels of adoption. The methodology ought to encompass an economic rationale for a chosen approach, coupled with an assessment framework for prognostic techniques. In their study, Wagner and Hellingrath (2019) discuss a challenge related to the definition of a business case, which has been found to have a negative correlation with adoption rates in manufacturing companies. As per the authors' assertion, it is imperative to establish a precise definition of the problem at hand, and the business case must demonstrate a lucid advantage. The process of identifying cases can prove to be challenging for many firms owing to a restricted comprehension. According to Loorpuu (2020), the development of a suitable business case serves as the basis for the implementation of PdM. However, due to a limited understanding of PdM, creating a business case can be a challenging task as it is difficult to quantify the effects of PdM. This lack of quantification is negatively correlated with the level of adoption.

The observation made above is consistent with the results of a consultancy report on the adoption of PdM in manufacturing firms. Specifically, the report found that 63% of the cases examined indicated that a significant barrier to the adoption of new technologies was the difficulty in identifying or developing a compelling business case (Bokrantz et al., 2017). PdM is commonly regarded as a project with a high level of risk due to the intangible nature of its costs and benefits, particularly with respect to the unreliable determination of budgetary costs. Additionally, the successful execution of PdM cannot be guaranteed. According to Wagner and Hellingrath (2019), the project necessitates significant initial investment and expenses.

Nevertheless, the actual economic advantage is observable only after a considerable period, thereby postponing the favorable outcomes.

In manufacturing firms, inadequate data management has been recognized as a hindrance to the effective adoption of PdM. The voluminous nature of big data sets, coupled with their diverse formats and structures, can pose significant challenges in comprehending them, unless they are appropriately labeled, structured, and maintained (Schmidt, 2018). The difficulties posed by the intricacies of real-time data, inconsistencies in data originating from the source, and inadequacies in data cleansing have been ascribed to organizations' insufficient comprehension and expertise in big data management (Riggins & Wamba, 2015).

The utilization of data originating from various PdM systems and operational domains is of great significance to maintenance and production operations. Its importance lies in its ability to facilitate diagnosis and prognosis, if it is comprehended and utilized effectively (Talukder, 2011). The expansion of continuous data poses significant challenges, such as effectively managing a substantial volume of data and devising more precise prognostic algorithms that integrate deterministic methodologies. This is perceived as a hindrance to the successful implementation of such approaches (Xu et al., 2016). Schmidt (2018) identified a deficiency in comprehensively viewing and comprehending equipment or assets, as well as isolated pockets of knowledge within an organization, which ultimately contribute to increased complexity. In an organizational context, information pertaining to equipment is collected by various functional units for distinct purposes, including but not limited to maintenance, quality assurance, and production. Homogeneous apparatus has the potential to be allocated across diverse channels, divisions, and manufacturing plants, resulting in the collection and evaluation of dispersed data in an autonomous manner. As a result, the authors draw the conclusion that the failure to apply lessons learned from one context to another context poses a challenge to the successful adoption of such lessons by firms.

Li et al. (2019) discovered that the adoption rates of PdM implementation are impacted by a deficiency of confidence in the analytical outcomes of big data. In instances of this nature, it is plausible for managers and practitioners within a manufacturing entity to encounter challenges in placing reliance on the inferences derived from PdM big data analytics outcomes. This could be attributed to conflicting interests in the utilization of big data, intricacy in comprehending the outcomes, or the caliber of the analytical results. This phenomenon has been observed due to the substitution of user experience with machine analysis. According to a consultancy report by Haarman et al. (2018), the absence of data analytics capabilities was identified as a hindrance to the adoption levels.

2.4 Research gap

The preceding empirical literature indicates that numerous studies akin to the present investigation have been carried out in various locations, yielding recommendations and proposed remedies. Nevertheless, no research has been conducted to specifically investigate the evaluation of the factors that impact the adoption and implementation of predictive maintenance technologies in organizations among small and medium-sized enterprises. Consequently, the data to be gathered from this investigation, along with the resulting conclusions and recommendations, will address the identified gap.

2.5 Conceptual framework

The conceptual framework of the present study elucidates the interconnection between the independent variables and the dependent variable. The study's independent variables encompassed User perception factor, Cost reduction factor, Job effectiveness factor, Technological factors, Individual factors, Economic factors and Effectiveness and efficiency (view Figure 1). The dependent variable under investigation was the Adoption and implementation of predictive maintenance technologies in organizations.

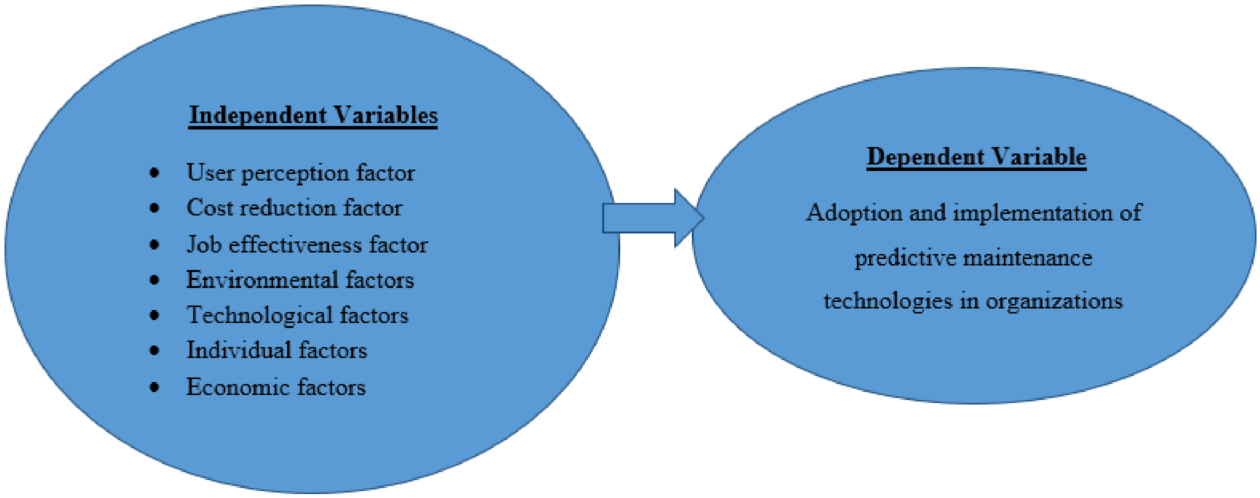

Figure 1: Conceptual Framework (Author, 2023)

2.5.1 Definition of variables

2.5.1.1 User perception factors

User perception is defined as the experiences, skills, and reactions of a person that come from the use or anticipated utilization of a product, system, or service in accordance with the International Organization for Standardization (ISO) standard on the ergonomics of human system interaction (Mirnig et al., 2015). This definition can be found in the User Perception section. According to the definition that is offered by ISO, user perception is comprised of a wide variety of characteristics such as feelings, beliefs, preferences, experiences, bodily and psychological reactions, behaviors, and achievements that appear before, during, and after the use of a product or service. The ISO identifies the system, the user, and the context of usage as the three most important variables that influence how a user perceives a product or service. It is to an organization's advantage to develop a habit of employing a variety of technologies with staff who are skilled in their use. However, if a company believes that a certain technology is much too complicated, it could decide against deploying a predictive maintenance technology system. According to Phelps et al. (2005), competence is a critical component that has a significant influence on the use of computerized systems. In this study, user perception will be operationalized using the definition provided by

ISO (Mirnig et al., 2015). According to this definition, user perception is the sum of an individual's experiences, skills, and reactions that result from the use or expected utilization of a product, system, or service. The definition will be used to guide the research presented here. The level of expertise, proficiency, and adaptability of the user is a critical factor in determining whether an organization will use a computerized system.

2.5.1.2 Costs (cost reduction factor, economic factors)

In economics, the word "cost" refers to the voluntarily surrender of objects, assets, resources, or moral rights that have a monetary value, with the intention of receiving a present or future benefit that is not inferior to the value at the moment of the surrender. This may be done to get something that is more valuable than what was surrendered. The total worth of the sacrifice is increased because of this procedure (Xu et al., 2016). When adapting CIAS, careful consideration of the cost aspect is very necessary to achieve the best possible balance between the projected advantages of the system and the costs of its development and execution [59]. According to the findings of study conducted by Elbeltagi et al. (2013), there is a correlation that can be directly attributed to the expense of implementing new technology. This conclusion was reached based on the findings of two different research. Because of the high initial costs of set up, some businesses are hesitant to use computerized accounting systems, which is understandable given the nature of the situation. The implementation of the system calls for the hiring of personnel who have received specialized education for it to function properly. Because of this, large costs are incurred for the purpose of training in order to retain competency in the use of hardware and software. This is necessary since fresh iterations of such technology are acquired to maximize the efficiency and productivity of computerized systems. The present research will make use of the definition provided by Haleem (2016), which states that the cost of computerized installation includes the expenses that are incurred in procuring equipment, the costs that are associated with assembling the equipment, and the expenses that are incurred in testing and starting up the system. This definition will serve as the basis for the research that will be carried out. The influence that the cost of a system has on whether it is accepted and used for its intended purpose is what gives it its relevance.

2.5.1.3 Technological factors

Research has indicated that the acceptance of innovation by an individual is influenced not only by their personal attitudes but also by the policies, approaches, and actions of the organization (Xu et al., 2016). According to Talukder's (2011) research, it is imperative for organizations to offer conducive circumstances, including the degree and nature of assistance extended to their staff, as these factors can significantly impact their adoption of innovative practices. The provision of training and support is conducive to facilitating conditions. The factors that contribute to the organization's effectiveness encompass training, managerial support, and incentives. The adoption of a technological innovation by employees can be motivated by organizational influences.

2.5.1.4 Individual factors

According to Xu et al. (2016) personal factors play a crucial role in the adoption of technological innovation. According to various studies, personal factors such as perceived benefits, personal innovativeness, prior experience, and enjoyment with innovation have a significant impact on employees' technology acceptance and continuous usage (Davis, 1989).

2.6 Chapter summary

The present chapter has centered on conducting a literature review of prior research studies conducted by other scholars on the factors that impact the implementation of intelligent predictive maintenance in manufacturing firms situated in the United Arab Emirates. The literature review was conducted to address the research question pertaining to the adoption of predictive maintenance. The review focused on various factors such as user perception, cost reduction, job effectiveness, environmental impact, technological advancements, individual factors, economic considerations, and effectiveness and efficiency in the adoption of predictive maintenance. Additionally, the review explored the complexity of adopting predictive maintenance, with a specific emphasis on technical skills, level of understanding, and communication. The forthcoming chapter centers on the methodology employed in the research.

Chapter 3 Research Methodology

3.1 Introduction

The present chapter explains the research design and methodology that were employed in the current research investigation. The framework was developed to assist the researcher in addressing the research questions that were identified. The chapter is structured into distinct sections that are categorized under subheadings such as research design, population and sampling design, data collection methods, research procedures, data analysis methods, validity and reliability, and ethical considerations of the research.

3.2 Research design

The term "research design" pertains to the comprehensive approach that has been chosen and implemented to conduct research. It is a concise and coherent blueprint that integrates various elements of the study to ensure that the research questions are adequately addressed through the collection, interpretation, analysis, and discussion of data (Xu et al., 2016). The research will employ a mixed-methods approach to collect and evaluate data from diverse qualitative and quantitative sources. The classification of research design can be delineated into three principal types of design. According to Patidar et al. (2017) the three types of research design are exploratory, descriptive, and causal. The application of exploratory research design is beneficial in situations where a researcher lacks clarity regarding the problems that may arise during the study. This approach facilitates the asking of open-ended questions to gain insights into the area of inquiry and comprehend the situation at hand (Venkatesh et al., 2003). The research design known as causal research, or explanatory research, is focused on the examination of a particular situation or problem with the objective of identifying causal relationships between the variables (Xu et al., 2016).

The descriptive research design is utilized to establish a definition and depiction of variable characteristics within a given situation. This design method accurately profiles a particular individual, group, event, or situation (Venkatesh et al., 2003). It is preferable to generalize study findings to a broader population based on a representative sample. The present study employed a descriptive research design utilizing a correlational approach to enhance comprehension of the association between independent and dependent variables (Xu et al., 2016). Furthermore, the data gathered pertains to individuals, organizations, settings, and phenomena, thereby characterizing a descriptive research design (Xu et al., 2016). The present investigation incorporated several independent variables, namely User perception factor Cost, reduction factor, Job effectiveness factor, Environmental factors, Technological factors, Individual factors, Economic factors, and Effectiveness and efficiency while the dependent variable was the adoption of smart predictive maintenance.

3.3 Population and sampling

The concepts of population and sampling design pertain to the identification of the intended study population and the methodology for selecting individual samples from the entirety of the target population.

3.3.1 Population

The concept of population in research refers to a collective group of individuals, objects, environments, organizations, institutions, events, and occurrences that share common characteristics and are of interest to the researcher (Xu et al., 2016). The group is distinguished from other individuals, institutions, and objects by these shared characteristics. The study's population comprised 108 participants who held positions in factory management (primarily plant/factory manager, production, and maintenance manager), production and maintenance engineering, and supervision across various manufacturing companies situated in the UAE.

3.3.2 Table

3.3.2.1 Target Population Distribution

Table 1 below presents details about the target population distribution. There is information about the name of company, factory location, and target population.

Table1 : Target Population Distribution

Name of company	Factory location	Target population
Abu Dhabi Oil Company	UAE	8
Emirates Steel Industries	UAE	8
Union Cement Company	UAE	8
Gulf Extrusions Co. LLC.	UAE	11
Dubai Aluminum Company Limited	UAE	8
Dubai Refreshments	UAE	8
Al Ghurair & Steel LLC	UAE	11
Julphar Gulf Pharmaceutical Industries	UAE	8
Nestle Middle East	UAE	8
Emirates Flaot Glass		11
Dubai Cable Company		8
Al Tayer Group		11
Abu Dhabi Polymers		8
TOTAL		108

3.3.3 Sampling design

The term "sampling design" pertains to the methodology or algorithm utilized by the researcher in the process of choosing elements from a given sample (Riggins & Wamba, 2015). The sampling design encompasses the sampling frame, sampling technique, and sample size utilized in this research investigation.

3.3.3.1 Sampling frame

According to Algabroun (2020), a sampling frame refers to a list of all items belonging to the population of interest or target population, from which the sample population is drawn. The present investigation employed a sampling frame comprising 108 participants from five distinct manufacturing facilities situated in the UAE.

3.3.3.2 Sampling technique

According to Algabroun (2020), a sampling technique refers to the methodology employed in the selection of a sample. The selection of an appropriate sampling technique is crucial to obtain a sample that is most representative. The field of sampling technique is commonly classified into two main categories, namely probability sampling and non-probability sampling. The probability sampling technique is commonly utilized in quantitative research, whereby the selection of sample subjects is based on known probabilities. The aforementioned methodology is subsequently deconstructed into various sampling techniques, namely: simple random, systematic random, stratified random, cluster, and multistage sampling technique (Bokrantz et al., 2017). Non-probability sampling is commonly employed in qualitative research, wherein participants are selected through non-random sampling methods and involve a degree of subjective judgement (Loorpuu, 2020). The sampling techniques under consideration are convenience sampling, judgmental sampling, quota sampling, and snowball sampling. The research employed a stratified random sampling methodology, which falls under the category of probability sampling techniques. The process of sampling entails the division of the entire population into several distinct and homogeneous groups, commonly referred to as strata. Samples are selected from each stratum through a process of simple random sampling (Zhang & Nuttall, 2011). The utilization of a sampling technique was implemented due to its ability to decrease survey expenses, increase the level of representation, and enhance overall efficiency. The study employed a stratification variable consisting of five distinct manufacturing factories.

3.3.3.3 Sample size

The concept of sample size refers to the quantity of individuals who are selected to participate in a population sample, which is intended to serve as a representative subset of the larger target population (Talukder, 2011). The determination of an appropriate sample size is a crucial aspect of statistical analysis. Inadequate sample sizes may result in invalid outcomes and an inaccurate representation of the population under investigation. Conversely, excessively large sample sizes may produce minimal margins of error and a more accurate representation of the population, but at a significant increase in cost and time required to conduct the research (Xu et al., 2016). According to Algabroun (2020), the ideal sample size is the one that satisfies the criteria of efficiency, representativeness, flexibility, and reliability. Therefore, considering the aforementioned factors, attaining a sample size that is highly representative is a crucial necessity for researchers conducting surveys, as it significantly impacts the cost and duration of the survey, as well as the precision of the sample estimation (Venkatesh et al., 2003).

Franciosi et al. (2020) have identified several factors that determine the appropriate sample size for a study. These factors include the level of confidence or certainty required in the representativeness of the data collected, the margin of error or desired level of accuracy, the size of the target population, and the type of analysis to be conducted on the collected data. The Taro Yamane statistical formula was employed to establish the sample size for the research study, given that the target population of the eight manufacturing companies in the UAE is known to be 108 respondents. Using such a formula has been found appropriate to justify the selected number of participants. The formula endeavors to mitigate the two most prevalent shortcomings that researchers encounter when determining sample size, namely, overlooking sampling error and non-response bias (Ye, 2018). The formula for Yamane is presented as follows:

Sample size e, n = N $= \frac{\mathrm{N}}{(1+\mathrm{Ne2})}$

Where; N= Population size

e= Margin of percent error required. For this study, the maximum margin of error that was is 5 percent to give a confidence level of 95 percent.

Using the formula to determine the sample size;

$n = 108 \div (1 + (108 * 0.05 * 0.05) = 85$

The study employed a sample size of 85 respondents, which was allocated proportionally to the population size of the different locations of the 5 manufacturing companies operating in UAE.

3.3.3.4 Sample size distribution

Table2 : Sample Size Distribution

Name of company	Factory location	Target population	Sample Size
Abu Dhabi Oil Company	UAE	8	6
Emirates Steel Industries	UAE	8	6
Union Cement Company	UAE	8	6
Gulf Extrusions Co. LLC.	UAE	11	9
Dubai Aluminum Company Limited	UAE	8	6
Dubai Refreshments	UAE	8	9
Al Ghurair & Steel LLC	UAE	11	6
Julphar Gulf Pharmaceutical Industries	UAE	8	6

Nestle Middle East	UAE	8	9
Emirates Flaot Glass		11	6
Dubai Cable Company		8	9
Al Tayer Group		11	6
TOTAL		108	

3.4 Data collection methods

The present study utilized primary data that was gathered through the implementation of a structured questionnaire. The survey was conducted using BUID surveys and disseminated to participants via electronic mail. The primary rationales behind opting for a structured questionnaire are as follows: firstly, it is comparatively cost-effective and enables a broader geographical coverage; secondly, it allows respondents to express their views in an unbiased manner, free from any influence by the researcher; and thirdly, each participant in the survey responds to the same set of questions in a predetermined sequence (Bokrantz et al., 2017). According to Franciosi et al. (2020), it is the prevailing method employed in business and management research.

The questionnaires utilized in this study employed a Likert-type scale consisting of five points, ranging from "strongly agree" (coded as 1) to "strongly disagree" (coded as 5). The utilization of a Likert scale was deemed appropriate for this quantitative research endeavor, as it necessitates the collection of ordinal data and is a commonly employed tool in numerous business-related investigations (Zhang & Nuttall, 2011). The survey instrument was partitioned into five distinct sections. The initial section of the questionnaire was dedicated to gathering demographic information, including gender, job title, educational attainment, and the duration of the organization's establishment. The second section of the study centered on the implementation of intelligent predictive maintenance, while the third section examined the impact of relative advantage on the adoption of predictive maintenance. Section four of the study examined the impact of compatibility on the adoption of predictive maintenance, while section five delved into the influence of complexity on the adoption of predictive maintenance.

3.5 Data analysis Method

Following the collection of data, it is crucial to undertake processing and analysis procedures to ensure its relevance in facilitating contemplated comparisons and analyses, as stated by Kothari (2004). The process involves various stages such as editing, grouping into homogeneous categories, coding, and tabulating data to facilitate analysis. The analytical process entailed the utilization of multiple regression. Subsequently, the processed data was subjected to both descriptive and inferential statistical analysis by the researcher. Descriptive statistical techniques facilitate the numerical depiction and comparison of variables. The study centered on fundamental statistical measures such as frequency, percentages, mode, mean, and standard deviation to analyze sample characteristics and patterns, specifically those related to central tendency and dispersion (Saunders et al., 2016). Inferential statistics encompasses the process of identifying relationships and variances among variables, utilizing multiple regression analysis. The statistical results were subsequently analyzed and presented in the results and findings section. The results were displayed using tables and figures. The multiple in the context of statistical analysis, involves the formulation of a mathematical model that incorporates multiple independent variables that are hypothesized to have a significant association with the dependent variable. The equation can be expressed in the following format:

- Adoption and implementation of predictive maintenance technologies in organizations = a + b1(User perception factor) + b2(Cost reduction factor) + b3(Job effectiveness factor) + b4(Environmental factors) + b5(Technological factors) + b6(Individual factors) + b7(Economic factors) + b8(Effectiveness and efficiency) + e
- where a is the intercept, b1 through b8 are the regression coefficients for each independent variable, and e is the error term.
- The regression coefficients (b1 through b8) represent the change in the dependent variable that results from a one-unit change in the corresponding independent variable, holding all other independent variables constant. For example, a positive coefficient

for "User perception factor" would indicate that a more positive user perception is associated with a higher adoption and implementation of predictive maintenance technologies, all else being equal.

The results of the multiple regression analysis can help us understand which independent variables are most strongly associated with the dependent variable, and how much of the variation in the dependent variable can be explained by the independent variables. We can also use the regression equation to make predictions about the adoption and implementation of predictive maintenance technologies based on the values of the independent variables.

3.5.1 Null hypothesis

None of the independent variables—"User perception factor," "Cost reduction factor," "Job effectiveness factor," "Environmental factors," "Technological factors," "Individual factors," "Economic factors," and "Effectiveness and efficiency"—has a sizable impact on the adoption and implementation of predictive maintenance technologies in organizations.

3.5.2 Alternative hypothesis

At least one of the independent factors—"User perception factor," "Cost reduction factor," "Job effectiveness factor," "Environmental factors," "Technological factors," "Individual factors," "Economic factors," or "Effectiveness and efficiency"—has a sizable impact on the adoption and implementation of predictive maintenance technologies in organizations.

The null hypothesis posits that the independent variables lack a significant impact on the dependent variable, whereas the alternative hypothesis contends that at least one independent variable exerts a significant effect on the dependent variable.

To evaluate the hypotheses, multiple regression analysis would be employed to ascertain the statistical significance of the relationship between the independent variables and the adoption and implementation of predictive maintenance technologies within organizations. In the context of multiple regression analysis, if the p-value linked with the F-statistic is lower than the predetermined level of significance (e.g., 0.05), the null hypothesis is rejected. This leads to the conclusion that a minimum of one independent variable has a significant impact on the adoption and implementation of predictive maintenance technologies in organizations. If the p-value exceeds the predetermined level of significance, it would be appropriate to retain the null hypothesis and infer that there is insufficient substantiation to indicate that any of the independent variables exert a noteworthy impact on the adoption and implementation of predictive maintenance technologies within organizational settings.

3.6 Validity and reliability of data

The fundamental aspects of ascertaining the excellence of a research study are the concepts of reliability and validity. According to Bousdekis et al. (2019), for a study to yield dependable, coherent, and pertinent findings, the data presented must possess both reliability and validity. Achieving reliability necessitates the utilization of standardized instruments for information collection and survey protocols that are intended to improve uniformity. Franciosi et al. (2020) define validity as the degree to which survey data is pertinent to the conclusion being made and is precise and comprehensive enough to substantiate the conclusion. The accuracy of research findings and the extent to which they measure the intended variables are determined by validity. The study ensured and attained both reliability and validity by scrutinizing inaccuracies or missing information throughout the data collection, maintenance, processing, and reporting stages. Additionally, proper sampling procedures were employed to obtain a representative sample, and standardized data collection instruments were carefully selected and utilized.

3.6.1 Reliability of the instrument

The investigator ascertained the dependability of the measuring tool through the implementation of a preliminary trial to evaluate the consistency and accuracy of the survey instruments. A pilot study was carried out with an oil company, wherein entrepreneurs were requested to complete a questionnaire and one representative from each business was interviewed. The objective of the study was to assess the comprehensibility of the questionnaire, minimize errors and time consumption during the completion of the questionnaire, and evaluate the effectiveness of the constructs covered. The researcher incorporated feedback from participants involved in the pre-testing phase to refine the research instruments.

3.6.2 Validity of the instrument

The study utilized a triangulation strategy to ensure validity, incorporating both data source triangulation and methodology triangulation. The researcher employed data triangulation methodology to gather information from various sources, including primary and secondary sources. Methodological triangulation is a research approach that involves the use of multiple data collection methods, such as face-to-face interviews, questionnaires, and document review.

3.7 Research ethical considerations

The significance of ethical considerations in research lies in the imperative need to uphold the dignity and respect of participants throughout the study. According to Franciosi et al. (2020) ethical considerations hold significant importance in research, encompassing aspects such as voluntary participation, non-infringement of participants' well-being, preservation of anonymity and confidentiality, and avoidance of deceit. During this investigation, ethical concerns were identified. Specifically, the researcher sought consent from the entrepreneurs prior to data collection, adhered to ethical considerations in the selection of data collection methods, exercised care in the presentation and interpretation of findings, and maintained proper citations and referencing practices.

3.8 Expected results

The study's results are anticipated to provide insight into the factors that impact the adoption and implementation of PdM within manufacturing enterprises in the UAE. The researcher hypothesized that various factors play a role in the adoption of PdM systems by companies. The research aims to conduct a comprehensive examination of the factors that influence the adoption and implementation of PdM in manufacturing firms in the UAE, as well as their impact on organizational performance. The present study aims to identify the key factors that contribute to the acceptance and implementation of PdM. Specifically, the research will examine the impact of corporate culture, leadership support, employee training, and technological capabilities on the success of PdM.

3.9 Chapter Summary

The present chapter outlines the research methodology that will be employed in the current study. This chapter encompasses various elements of research methodology, including research design, population and sampling design, data collection, research procedures, and data analysis methods. The study employed a mixed methods research design to gather, assess, and analyze data. The data was gathered through the administration of questionnaires and subjected to both quantitative and qualitative analysis.

Chapter 4 RESULTS AND ANALYSIS

4.1 Introduction

This chapter presents the results obtained from a survey conducted online with participants from several companies in the UAE. All the data are reported, and relevant conclusions are reached in relation to the initially posed research objectives and questions. Also, the respective research findings are analyzed using SPSS and multiple regression methodology. At the same time, relevant qualitative findings obtained from secondary research (literature review) are analyzed by presenting in-depth interpretation of the major themes related to the research topic.

4.2 Research Findings

In describing the sample of participants in this study, certain demographic characteristics were explored. These characteristics were illustrated as gender, age, occupation, education, and working experience. The tables (Table 3 and Table 4) below represent specific information about the mentioned demographics.

Table 3: Gender (Author, 2023)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	67	66.3	66.3	66.3
	Female	34	33.7	33.7	100.0
	Total	101	100.0	100.0	

As seen in the table, there were 66% males and 33.7% females who participated in this research. This shows that male participants were prevailing, even though this demographic characteristic did not have a significant statistical influence on the results.

Table 4: Age (Author, 2023)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	20-29 years	10	9.9	9.9	9.9
	30-39 years	47	46.5	46.5	56.4
	40-49 years	39	38.6	38.6	95.0
	50 years and above	5	5.0	5.0	100.0
	Total	101	100.0	100.0	

The age group of the respondents was from 29 to 50 years and above. According to the frequency analysis of the age group, 10 of the respondents were from the age group of 20-29 years. Moreover, 47 respondents were from the age group of 30-39 years, 39 respondents were from the age group of 30-49 years, and the other five respondents were in the age group of over 50 years of age. Based on these results, it is apparent that most of the participants were middle-aged, which suggested that they had a significant working experience (Table 5).

Table 5: Designation in the Organization (Author, 2023)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	manager	43	42.6	43.0	43.0
	supervisor	16	15.8	16.0	59.0
	engineer	32	31.7	32.0	91.0
	plant / general manager	9	8.9	9.0	100.0
	Total	100	99.0	100.0	
Missing	System	1	1.0		
Total		101	100.0		

The above table shows the results for the designation of the respondents in the organization in which they are working. According to these results, 43 respondents are working as a manager in their organization, 16 are working as a supervisor, 32 respondents are working as an engineer, and the rest nine respondents are working as plant/ general manager in their organization. Most of the participants (42.6%) are working in managerial positions, illustrating their commitment to manage different organizational issues and employee relations.

Table 6: Participants' Highest Level of Education (Author, 2023)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	degree	18	17.8	17.8	17.8
	PG degree	71	70.3	70.3	88.1
	certificate / diploma	12	11.9	11.9	100.0
	Total	101	100.0	100.0	

The respondents' level of education is an important aspect in this research because education is a relevant indicator of knowledge, working experience, and ability to complete certain tasks successfully. When it comes to analyzing the participants' education level, it turned out that 18 respondents have a degree in education whereas 12 respondents have certificate/ diploma education, and 71 respondents have post graduate education (Table 6). This shows that all the respondents were educated and clearly recognized the importance of research.

Table 7: Working Experience in the Organization (Author, 2023)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-5 years	38	37.6	38.0	38.0
	6-10 years	62	61.4	62.0	100.0

	Total	100	99.0	100.0	
Missing	System	1	1.0		
Total		101	100.0		

The above table shows the results for the working experience of the respondents. According to these results, 38 respondents have an experience of 1-5 years, while 62 respondents have experience of 6-10 years. In other words, most participants have a sufficient experience in diverse organizational settings (Table 7). This aspect illustrates that the respective individuals are adequately prepared to recognize different organizational issues or factors that may influence the adoption and implementation of predictive maintenance technologies in organizations.

4.2.1 Descriptive analysis

Table 8 below presents descriptive statistics based on the results obtained from a survey with the participants. The factors explored in the study were identified as user perception, cost reduction, job effectiveness, environmental, technological, individual, economic, and effectiveness and efficiency factors. In relation to the statements presented by participants, it has been illustrated that they mostly agreed with those statements, considering the standard deviation of .86363 for the ‘strongly agree’ dimension.

Table 8: Descriptive Statistics (Author, 2023)

	N	Mean	Std. Deviation
7. To what degree has this organization implemented intelligent predictive maintenance within its operational framework? Please mark the appropriate cell that best represents the level of implementation within your organization.			
7.1. STRONGLY DISAGREEE vs STRONGLY AGREE	100	4.0400	.86363
8. To what degree has your organization been affected by the smart predictive maintenance technologies factors listed below? Please mark the appropriate cell that closely represents the level of implementation within your organization. Use a scale of 1- 5			
8.1. User perception factors	101	4.0000	.72111
8.2. Cost reduction factors	101	3.9406	.74595
8.3. Job effectiveness factors	101	3.8812	.75216
8.4. Environmental factors	101	3.8911	.85908
8.5. Technological factors	100	3.9300	.80723
8.6. Individual factors	101	3.9109	.76288
8.7. Economic factors	100	3.9100	.75338
8.8. Effectiveness and efficiency	101	4.1485	.81714

9. Relative advantage refers to the extent of the added value or benefit that an organization can obtain by adopting a new technology or innovation, as opposed to maintaining the current state of affairs. The degree to which the novel technology is perceived			
9.1. The manufacturing industry tends to readily adopt predictive maintenance technology due to its perceived potential to increase profitability.	101	4.0495	.66897
9.2. The adoption of predictive maintenance technology is perceived to enhance cost reduction for equipment spares.	101	3.8416	.70332
9.3. The adoption rate of predictive maintenance technology is positively correlated with the perception that it enhances a firm's productivity.	101	3.8911	.91543
9.4. The adoption rate of predictive maintenance technology is higher when it is perceived to enhance a firm's competitive advantage in the manufacturing industry.	100	3.7500	.86894
9.5. The adoption of predictive maintenance technology is perceived to enhance warehouse management for equipment spares.	101	3.6436	.84361
9.6. Predictive maintenance technology that is perceived to enhance just-in-time maintenance is easily adopted in the manufacturing industry.	101	3.7624	.82642
9.7. The rapid adoption of predictive maintenance technology in the manufacturing industry is attributed to its perceived ability to improve job effectiveness.	101	3.7624	.88486

9.8. The adoption rate of predictive maintenance technology is higher when it is perceived to result in a reduction of manufacturing costs.	101	3.7921	.91997
9.9. The adoption of predictive technology in the manufacturing industry is facilitated by the perception that it enhances equipment uptime.	101	3.8218	.85318
9.10. The adoption rate of predictive maintenance technology is higher when it is perceived to have a positive impact on extending the lifespan of equipment.	101	3.9505	.88743
9.11. The adoption rate of predictive maintenance technology is higher when it is perceived to result in enhanced electrical efficiency of equipment and energy conservation.	101	3.7822	.93385
10. Please indicate the degree to which compatibility has impacted the implementation of smart predictive maintenance in your organization by selecting the appropriate cell and placing a checkmark (√) within it. Use a scale of 1- 5 where: 1 = Strongly Disagree			
10.1. The adoption of predictive maintenance technology in the manufacturing industry is facilitated by its perceived compatibility with existing equipment technology.	101	3.9901	.76805
10.2. The manufacturing industry can readily adopt predictive maintenance technology that is compatible with its existing information and communication technology infrastructure.	101	3.8416	.84537
10.3. The swift adoption of predictive maintenance technology in the manufacturing industry is facilitated by its compatibility with pre-existing information security systems.	101	3.8020	.84876

10.4. The adoption of predictive maintenance technology is facilitated when it is perceived to be compatible with the existing organizational strategy.	101	3.6733	1.02087
10.5. The adoption rate of predictive maintenance technology is positively influenced by the perception of top management support.	100	3.8800	.87939
10.6. The adoption rate of predictive maintenance technology is higher when it receives support from the entire organization.	101	3.8218	.94230
10.7. The rate of adoption of predictive maintenance technology is positively correlated with the perceived adaptability of employees to novel technologies and changes.	101	3.8119	.89121
10.8. The expeditious adoption of predictive maintenance technology within an organization is contingent upon its alignment with the organization's culture and values, as perceived by its members.	101	3.8020	.70739
10.9. The manufacturing industry readily adopts predictive maintenance technology that involves end user participation.	101	3.9208	.80849
10.10. The expeditious adoption of predictive maintenance technology is facilitated by the presence of supportive policies from both business and government entities.	101	3.9703	.89950
10.11. The manufacturing industry has readily embraced the utilization of predictive maintenance technology, which has already been recognized and implemented.	101	4.0198	.78715
Valid N (listwise)	0		

4.2.2 Adoption and implementation regression

Table 9: Model Summary for Adoption (Author, 2023)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.460[a]	.212	.141	.31388	.212	3.018	8	90	.005

a. Predictors: (Constant), 8.8. Effectiveness and efficiency, 8.5. Technological factors, 8.2. Cost reduction factor, 8.6. Individual factors, 8.3. Job effectiveness factor, 8.7. Economic factors, 8.4. Environmental factors, 8.1. User perception factor

Table 10: ANOVA (Author, 2023)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.379	8	.297	3.018	.005[b]
	Residual	8.867	90	.099		
	Total	11.246	98			

a. Dependent Variable: Adoption

b. Predictors: (Constant), 8.8. Effectiveness and efficiency, 8.5. Technological factors, 8.2. Cost reduction factor, 8.6. Individual factors, 8.3. Job effectiveness factor, 8.7. Economic factors, 8.4. Environmental factors, 8.1. User perception factor

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	2.582	.291		8.870	.000	2.004	3.160		
	8.1. User perception factor	.034	.069	.072	.488	.626	-.104	.172	.401	2.491
	8.2. Cost reduction factor	-.020	.071	-.044	-.284	.777	-.162	.121	.357	2.803
	8.3. Job effectiveness factor	.093	.057	.207	1.642	.104	-.020	.206	.554	1.806
	8.4. Environmental factors	.033	.052	.083	.630	.530	-.070	.135	.508	1.968

8.5. Technological factors	.047	.050	.112	.941	.349	-.052	.145	.621	1.611
8.6. Individual factors	-.012	.046	-.027	-.258	.797	-.104	.080	.824	1.214
8.7. Economic factors	.016	.053	.035	.300	.765	-.089	.120	.642	1.559
8.8. Effectiveness and efficiency	.120	.046	.290	2.608	.011	.028	.211	.709	1.410

a. Dependent Variable: Adoption

As seen in the tables above, the value of R^2 shows the total effect of the independent variable. The R^2 is 0.212, which shows that 2.12% of the maintenance technology factors influence the adoption of predictive maintenance technologies in organization. Since the R^2 is less than 50%, this illustrates a less significant effect of maintenance technology factors on the adoption and implementation of predictive maintenance technologies in organizations. The ANOVA table represents the overall significance of the retrieved data. The significance level or p-value of the study is 0.000 and is less than 0.05. In this way, it can be concluded that the significance of the reported research findings is quite high.

In considering the adoption of predictive maintenance technologies in organizations, the following combination of results has been reported: 2.582 + 0.0341(User perception factor) + -0.020 (Cost reduction factor) + 0.093(Job effectiveness factor) + 0.033(Environmental factors) + 0.047(Technological factors) + -0.012(Individual factors) + 0.018(Economic factors) + 0.120(Effectiveness and efficiency) + 0.291. According to the regression analysis performed, the independent variable effectiveness and efficiency has the p-value 0.011, which is less than

0.05 and shows that effectiveness and efficiency influence the adoption of predictive maintenance technologies more compared to other factors.

Table 11: Model Summary for Implementation (Author, 2023)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.654[a]	.427	.376	.34952

a. Predictors: (Constant), 8.8. Effectiveness and efficiency, 8.3. Job effectiveness factor, 8.4. Environmental factors, 8.2. Cost reduction factor, 8.1. User perception factor, 8.7. Economic factors, 8.5. Technological factors, 8.6. Individual factors

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.198	8	1.025	8.389	.000[b]
	Residual	10.994	90	.122		
	Total	19.193	98			

a. Dependent Variable: implementation

b. Predictors: (Constant), 8.8. Effectiveness and efficiency, 8.3. Job effectiveness factor, 8.4. Environmental factors, 8.2. Cost reduction factor, 8.1. User perception factor, 8.7. Economic factors, 8.5. Technological factors, 8.6. Individual factors

Coefficients[a]

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1 (Constant)	2.169	.251		8.636	.000		

8.1. User perception factor	.032	.030	.086	1.062	.291	.959	1.043
8.2. Cost reduction factor	.052	.030	.146	1.750	.084	.919	1.088
8.3. Job effectiveness factor	.097	.027	.295	3.559	.001	.928	1.077
8.4. Environmental factors	.087	.027	.270	3.241	.002	.917	1.090
8.5. Technological factors	.083	.030	.236	2.791	.006	.890	1.124
8.6. Individual factors	.103	.033	.263	3.102	.003	.889	1.125
8.7. Economic factors	.065	.037	.149	1.778	.079	.903	1.107
8.8. Effectiveness and efficiency	.016	.023	.055	.681	.498	.962	1.039

a. Dependent Variable: implementation

As illustrated in the tables above, the value of R^2 shows the total effect of the independent variable. The R^2 is 0.645, which indicates that 64.5 % of the included maintenance technology factors influence the implementation of predictive maintenance technologies in organizations. The R^2 is more than 60%, which shows a substantial effect of maintenance technology factors on the implementation of predictive maintenance technologies. The significance level or p-value of the study is 0.000 for all the factors and is less than 0.05, implying that the data of the study is significant, and the hypothesis is accepted.

In considering the implementation of predictive maintenance technologies in organizations, the following combination of results has been reported: 2.169 + 0.032(User perception factor) + 0.052(Cost reduction factor) + 0.097(Job effectiveness factor) + 0.087(Environmental factors) + 0.083(Technological factors) + 0.103(Individual factors) + 0.065(Economic factors) + 0.106(Effectiveness and efficiency) + 000. According to the regression analysis performed, all the independent variables, respectively maintenance technology factors, influence the implementation of predictive maintenance technologies in organizations, as the p-value of all the factors is less than 0.05.

4.2.3 Analysis of the Research Findings

The results reported in the previous section showed that the sample of participants was mostly represented by male respondents. This aspect indicates that male employees are more prevailing in UAE organizations compared to female employees. Such gender imbalance may have certain implications for social equity and addressing the gender pay gap in organizations. However, it is found statistically irrelevant in this study since it was not considered crucial in determining participants' perceptions of the factors which influenced the adoption and implementation of predictive maintenance technologies in organizations. Yet the demographic factors of age, education, and experience in the organization presented significant information about the knowledge and strategic orientation of participants in this study. It has been concluded that the respective survey respondents were educated and demonstrated a relevant, positive attitude to bringing their working experience to the next level by recognizing the important role of certain factors affecting the adoption and implementation of predictive maintenance technologies in organizations.

All the factors included for multiple regression analysis in this study were found important for both adoption and implementation of predictive maintenance technologies in organizations. The user perception factor implies that any change or action planned in organizations should take place with user needs in mind. This means that leaders are expected to listen to the distinct views and perspectives shared by users because they experience first-hand the effects of the technological solutions being provided. In relation to the cost reduction factor, organizations are focused on adopting effective measures that could decrease their operational costs while introducing a wide range of technological solutions. The job effectiveness factor is also found important in this study, as the use of predictive maintenance technologies in organizations can help employees complete their job tasks more effectively. The emphasis is on understanding how the adoption and implementation of predictive maintenance technologies in organizations is seen as a proactive and dynamic approach to equipment management, which can significantly benefit business entities.

Environmental factors are also discussed to be an important determinant of the adoption and implementation of predictive maintenance technologies in organizations. It appears that good maintenance practices lead to effective problem-solving of key economic, environmental, and social problems. It is further found in the study as well as from performing a qualitative analysis of the literature that technological factors play a significant role in determining the precise way in which new technologies can be developed for various predictive tools in organizations. While individual factors related to the adoption and implementation of predictive maintenance technologies may vary, as shown from a qualitative analysis of the literature, the importance of economic factors has been emphasized in this study. In other words, key stakeholders in different organizations in the UAE have thoroughly considered the cost of adopting and implementing the mentioned technological solutions to enhance organizational performance. From this perspective, the factor identified as effectiveness and efficiency was highly rated in this study, implying relevant possibilities to improve different operations within organizations.

As noted, all the mentioned factors were found important to enhance the adoption and implementation of predictive maintenance technologies in organizations. Yet certain dimensions such as environmental factors and effectiveness and efficiency were discussed to be crucial to support organizations' predictive maintenance practices. Since predictive maintenance is considered in a more holistic way, it is important for key stakeholders in UAE organizations to approach the adoption and implementation process with greater attention to detail, considering the long-term benefits involved. In this context, it has been concluded that the consistency of stakeholders is crucial to achieving optimal results in terms of developing and implementing relevant predictive maintenance technologies.

4.3 Summary

This chapter presents the research findings obtained from an online questionnaire with participants who were recruited from different companies in the UAE. The research subjects were asked relevant questions to determine the factors that played an important role in the adoption and implementation of predictive maintenance technologies in organizations. Also, the answers provided to these questions helped the researcher conclude that the explored factors significantly improved organizational performance. After presenting the research findings, using SPSS and multiple regression methodology, the researcher analyzed the results and presented relevant insights for practice.

Chapter 5 CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter summarizes the main conclusion reached in the study. It also provides feasible recommendations to improve the functioning of UAE organizations in relation to the adoption and implementation of predictive maintenance technologies. At the same time, the chapter contains relevant information about implications for future research, as certain horizons might be further explored to present more conclusive results about the research topic.

5.2 Conclusion

In relation to the first research question posed in this paper, it has been illustrated that a wide range of factors influenced the adoption and implementation of predictive maintenance technologies in UAE organizations. The user perception factor was adequately explored to conclude that users' perspectives were found important in directing specific strategic actions in organizations. In other words, UAE organizations may need to become more flexible in considering the broad views and suggestions for improvement expressed by individuals. In this way, the notion of diversity may further emerge at the adoption and implementation stages, implying that diverse perspectives reflect the precise interests and expectations of employees.

The cost reduction factor was also considered a prerequisite for the facilitated adoption and implementation of predictive maintenance technologies in organizations. Business entities in the UAE were concerned with reducing operational costs while considering the utilization of the respective technological solutions. This means that the cost reduction factor was directly linked to improved profitability of organizations, as they may learn how to enhance resource utilization in dynamic organizational settings.

The job effectiveness factor was perceived as an important aspect contributing to the enhanced adoption and implementation of predictive maintenance technologies in organizations. In other words, users considered the importance of improving different effectiveness parameters of job tasks. From this perspective, the innovative nature of predictive maintenance technologies suggests promising opportunities to optimize the job as a whole, relying on users' engagement and motivation to explore different paths to success in the constantly developing workplace.

The other factors that were found important for the adoption and implementation of predictive maintenance technologies in UAE organizations were described as environmental, technological, individual, and economic factors as well as effectiveness and efficiency factors. It has been concluded that the combination of these factors led to a more thorough understanding of the precise organizational conditions, user needs, and expectations pertaining to the adoption and implementation stages of such technological solutions. The interlinks between the explored factors indicated that all dimensions are connected to create a coherent image of the adoption and implementation process in organizations.

In addressing the second research question developed in this study, it is found that the factors influencing predictive maintenance technology adoption positively affected organizational performance. Since key stakeholders in UAE organizations assumed a proactive approach to emphasize the importance of using predictive maintenance technologies, the focus was on enhancing organizational performance. Such improved performance was linked to enhanced job motivation and high productivity, implying that organizations which adopted predictive maintenance technologies were successful in gaining a strong competitive edge. In other words, the emphasis on adopting and implementing predictive maintenance technologies in UAE organizations suggested the key role of leadership differentiation in achieving long-term strategic goals pertaining to significantly improved organizational performance.

5.3 Recommendations

Even though the factors explored in this study were found to positively affect the adoption and implementation of predictive maintenance technologies in UAE organizations and improved organizational performance, specific recommendations should be considered to achieve more optimal results in the long term. The path to establish and sustain success with predictive maintenance technologies is related to the development of innovative maintenance strategies. The adoption of a new maintenance strategy is always associated with various intense decisions that should be made at a certain point. For instance, organizational leaders usually consider the feasibility of such maintenance strategies, particularly in terms of ensuring cost-effectiveness. Thus, a relevant recommendation to organizational leaders of UAE organizations is to conduct a comprehensive assessment of available assets. It is important to determine the most essential organizational assets because this could guide future strategic decisions related to the adoption and implementation of predictive maintenance technologies.

It is further recommended to key stakeholders in UAE organizations to thoroughly evaluate their needs prior to deciding to invest substantial capital in predictive maintenance solutions. It is important to find out whether the respective solutions are optimal for the type of business operations carried out across organizations. For example, the size of those operations should be adequately considered, along with the complexity of the equipment involved in the adoption and implementation processes as well as the precise cost of downtime. It is crucial to determine if the adoption and implementation of predictive maintenance technologies could add a substantial value to organizations' operations.

Investing in skilled and qualified personnel is another important recommendation that should be further examined. It is apparent that the adoption and implementation of complex predictive maintenance technologies require that employees demonstrate a variety of skills and strategic preparedness to deliver optimal outcomes. It is expected that employees should be trained to analyze and interpret complex datasets, which is crucial in making informed decisions about diverse maintenance needs across organizations.

Another recommendation that may be provided to key stakeholders in UAE organizations is to ensure a high level of data security and privacy while adopting and implementing predictive maintenance technologies. The utilization of predictive maintenance solutions is linked to a large volume of data which is consistently collected to support stakeholders' decision-making processes. Such data should be secure and reliable and should comply with strict regulations pertinent to the country of operations, particularly the UAE.

The recommendation of raising awareness about the benefits of predictive maintenance technologies in organization should be adequately considered as well. From this perspective, employees should be educated and trained on the multiple advantages associated with the utilization of these technological solutions. As employees would be sufficiently prepared to implement these solutions in practice, the value added to different business operations is expected to be maximized in the long term.

5.4 Implications for Future Research

An important implication for future research that may be considered is related to the use of different research methodology. Even though the utilization of quantitative research is considered relevant in presenting statistically significant relationships between the variables, the use of qualitative research or mixed methods research may contribute to presenting more in-depth insights into the factors leading to the adoption and implementation of predictive maintenance technologies. For instance, future researchers may decide to use semi-structured interviews as a data collection method, as the focus would be on collecting substantial information about participants' lived experiences of the research topic. As the sample for such interviews is expected to be small, future researchers may pay more significant attention to the distinct perspectives and opinions shared by each individual participant.

Another implication for future research is associated with opportunities to improve the cross-cultural parameters of conducting a similar study. This means that other researchers may decide to extend the research on the factors pertaining to the adoption and implementation of predictive maintenance technologies to different geographical regions or countries. For example, it would be important to conduct comparative research on two countries from the same region, respectively the Gulf Cooperation Council (GCC) region. In this way, it could be possible to find out differences in adoption and implementation factors, which could encourage key stakeholders in organizations to learn from the constant exchange of important ideas and perspectives on the utilization of predictive maintenance technologies.

References

Algabroun, H. (2020). *On the development of a new digitalised maintenance approach for factories of the future*. Doctoral dissertation, Linnaeus University Press. DOI: 10.1108/JQME-04-2019-0039:2-20

Alsyouf, I. (2007). The role of maintenance in improving companies' productivity and profitability. *International Journal of Production Economics*, *105*(1), 70-78. DOI: 10.1016/j.ijpe.2004.06.057

Bokrantz, J., Skoogh, A., Berlin, C., & Stahre, J. (2017). Maintenance in digitalized manufacturing: Delphi-based scenarios for 2030. *International Journal of Production Economics*, *191*(1), 154–169. DOI:10.1016/j.ijpe.2017.06.010

Bousdekis, A., Apostolou, D., & Mentzas, G. (2019). Predictive maintenance in the 4th industrial revolution: Benefits, business opportunities, and managerial implications. *IEEE Engineering Management Review*, *48*(1), 57-62. DOI: 10.1109/EMR.2019.2958037

Carnero, M.C., & Gómez, A., 2017. Maintenance strategy selection in electric power distribution systems. *Energy, 129*, 255–272. DOI: 10.1016/j.energy.2017.04.100

Cho, Y., Hwang, J., & Lee, D. (2012). Identification of effective opinion leaders in the diffusion of technological innovation: A social network approach. *Technological Forecasting and Social Change*, *79*(1), 97-106. DOI: 10.1016/s0019-8501(99)00060-7

Compare, M., Baraldi, P., & Zio, E. (2019). Challenges to IoT-enabled predictive maintenance for industry 4.0. *IEEE Internet of Things Journal*, *7*(5), 4585-4597. DOI: 10.1109/JIOT.2019.2957029

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340. DOI: 10.2307/249008

Duffy, V. G. (Ed.). (2012). *Advances in Human Aspects of Healthcare*. CRC Press.

Elbeltagi, I., Hardekar, G., Al Sharji, Y., & Elsetouhi, A. (2013). The role of the owner manager in SMEs' adoption of information and communication technology in the United Arab Emirates. *Journal of Global Information Management*, *21*(2), 23-50. DOI: 10.4018/jgim.2013040102

Elliott, R. K. (1992). The third wave breaks on the shores of accounting. *Accounting Horizons*, *6*(2), 61. DOI: 10.1287/mnsc.35.8.982

Erol, S., Schumacher, A., & Sihn, W. (2017). Strategic guidance towards Industry 4.0 – a three-stage process model. *International Conference on Competitive Manufacturing*. Stellenbosch.

Evans, C. R. (1979). *The mighty micro: The impact of the computer revolution* (pp. 47-8). Gollancz.

Franciosi, C., Voisin, A., Miranda, S., Riemma, S., & Iung, B., (2020). Measuring maintenance impacts on sustainability of manufacturing industries: From a systematic literature review to a framework proposal. *Journal of Cleaner Production, 260*, 121065. DOI: 10.1016/j.jclepro.2020.121065

Fritsch, S. (2011). Technology and global affairs. *International Studies Perspectives*, *12*(1), 27-45. Oxford University Press.

Gebremichael, T., Ledwaba, L. P., Eldefrawy, M. H., Hancke, G. P., Pereira, N., Gidlund, M., & Akerberg, J. (2020). Security and privacy in the Industrial Internet of Things: Current standards and future challenges. *IEEE Access*, 152351-152366. DOI:10.1109/ACCESS.2020.3016937

Golightly, D., Kefalidou, G., & Sharples, S. (2018). A cross-sector analysis of human and organizational factors in deploying data-driven predictive maintenance. *Information Systems and e-Business Management*, *16*, 627-648. DOI: 10.1007/s10257-017-0343-1

Haarman, M., de Klerk, P., Decaigny, P., Mulders, M., Vassiliadis, C., Sijtsema, H., & Gallo, I. (2018). Predictive maintenance 4.0-beyond the hype: PdM 4.0 delivers results. *PricewaterhouseCoopers and Mannovation*. Retrieved from https://www.pwc.de/de/industrielle-produktion/pwc-predictivemaintenance-4-0.pdf

Haleem, A. (2016). The factor affecting is computerized accounting system with the reference to government department in the Ampara District. *EPRA*.

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of Management Information Systems*, *16*(2), 91-112. DOI: 10.1080/07421222.1999.11518247

Ingemarsdotter, E., Jamsin, E., Kortuem, G., & Balkenende, R. (2019). Circular strategies enabled by the Internet of Things-A framework and analysis of current practice. *Sustainability, 11*, 5689. DOI: 10.3390/su11205689

Jin, X., Weiss, B. A., Siegel, D., & Lee, J. (2016). Present status and future growth of advanced maintenance technology and strategy in US manufacturing. *International Journal of Prognostics and Health Management*, *7*. DOI: 10.36001/ijphm.2016.v7i3.2409

Kaminski, J. (2011). Diffusion of innovation theory. *Canadian Journal of Nursing Informatics*, *6*(2), 1-6. Retrieved from https://cjni.net/journal/?p=1444

Karuppiah, K., Sankaranarayanan, B., & Ali, S. M. (2021). On sustainable predictive maintenance: Exploration of key barriers using an integrated approach. *Sustainable Production and Consumption*, *27,* 1537-1553. DOI: 10.1016/j.spc.2021.03.023

Kothari, C. R. (2004). *Research methodology: Methods and techniques*. New Age International Publishers.

Lee, S. M., Lee, D., & Kim, Y. S. (2019). The quality management ecosystem for predictive maintenance in the Industry 4.0 era. *International Journal of Quality Innovation*, *5*, 1-11. DOI: 10.1186/s40887-019-0029-5

Li, S., Peng, G. C., & Xing, F. (2019). Barriers of embedding big data solutions in smart factories: Insights from SAP consultants. *Industrial Management & Data Systems, 119*(5), 1147-1164. DOI: 10.1108/IMDS-11-2018-0532

Loorpuu, A. (2020). Adoption of AI Based Predictive Maintenance Technologies in the manufacturing industry: Research to determine and develop the suitable best practices reference checklist to facilitate the adoption of artificial intelligence predictive maintenance technologies. *Repository*. Retrieved from https://repository.tudelft.nl/islandora/object/uuid%3A1db63388-3c42-4003-af7bfe09085e25c3

Mirnig, A. G., Meschtscherjakov, A., Wurhofer, D., & Meneweger, T. (2015). A formal analysis of the ISO 9241-210 definition of user experience. *33rd Annual ACM Conference*. DOI: 10.1145/2702613.2732511

Navas, M. A., Sancho, C., & Carpio, J. (2020). Disruptive maintenance engineering 4.0. *International Journal of Quality & Reliability Management*, *37*(6/7), 853-871. DOI: 10.1108/IJQRM-09-2019-0304

NS Energy (2020). *ADNOC completes first phase of AI-based predictive maintenance project*. Retrieved from https://www.nsenergybusiness.com/news/adnoc-completes-ai-predictive-maintenance-project/

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404-414. DOI: 10.1016/j.chb.2016.03.0

Ozer, M. (2000). Information technology and new product development: Opportunities and pitfalls. *Industrial Marketing Management*, *29*(5), 387-396.

Palazzeschi, L., Bucci, O., & Fabio, A. D. (2018). Re-thinking innovation in organizations in the Industry 4.0 scenario: New challenges in a primary prevention perspective. *Frontiers in Psychology*, *9*(30). DOI:10.3389/fpsyg.2018.00030

Patidar, L., Soni, V. K., & Soni, P. K. (2017). Maintenance strategies and their combine impact on manufacturing performance. *International Journal of Mechanical and Production Engineering Research and Development*, *7*(1), 13-22.

Phelps, R., Hase, S., & Ellis, A. (2005). Competency, capability, complexity and computers: Exploring a new model for conceptualizing end-user computer education. *British Journal of Educational Technology*, *36*(1), 67-84. DOI: 10.1111/j.1467-8535.2005.00439.x

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega*, *27*(4), 467-484. DOI: 10.1016/s0305-0483(98)00071-1

Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications: A technology-organisation-environment model. *Journal of Small Business and Enterprise Development*, *20*(4), 735-753. DOI: 10.1108/jsbed-12-2011-0035

Read, W. H. (1996). Managing the knowledge-based organization: Five principles every manager can use. *Technology Analysis & Strategic Management*, *8*(3), 223-233. DOI: 10.1080/09537329608524247

Riggins, F. J., & Wamba, S. F. (2015). Research directions on the adoption, usage and impact of the Internet of Things through the use of Big Data Analytics. *2015 48th Hawaii International Conference on System Sciences* (pp. 1530-1605). Hawaii, USA: IEEE Computer Society. DOI:10.1109/HICSS.2015.186

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Sadeghi, A.-R., Wachsmann, C., & Waidner, M. (2015). Security and privacy challenges in Industrial Internet of Things. *2015 52nd ACM/EDAC/IEEE Design Automation Conference* (pp. 1-6). IEEE. DOI:10.1145/2744769.2747942

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students*. Pearson.

Schallehn, H., Strahle, J., Seuring, S., & Freise, M. (2018). Customer experience creation for after-use products: A product-service systems-based review. *Journal of Cleaner Production, 210*. DOI: 10.1016/j.jclepro.2018.10.292

Schmidt, B. (2018). Toward Predictive Maintenance in a cloud manufacturing environment (*Doctoral Dissertation*). University of Skövde 2018. Skövde, Sweden: University of Skövde 2018. Retrieved from http://his.divaportal.org/smash/get/diva2:1203231/FULLTEXT01.pdf

Shafiee, M. (2015). Maintenance strategy selection problem: An MCDM overview. *Journal of Quality in Maintenance Engineering, 21*(4), 378-402. DOI:10.1108/JQME-09-2013-0063

Shamim, S., Cang, S., Yu, H., & Li, Y. (2017). Management approaches for Industry 4.0: A human resource management perspective. *2016 IEEE Congress on Evolutionary Computation (CEC*), 16, pp. 5309 -5316. Vancouver, BC, Canada. DOI:10.1109/CEC.2016.7748365

Sony, M., & Naik, S. (2018). Key ingredients for evaluating Industry 4.0 readiness for organizations: A literature review. *Benchmarking: An International Journal, 27*(7), 2213-2232. DOI:10.1108/BIJ-09-2018-0284

Spaargaren, G. (2011). Theories of practices: Agency, technology, and culture: Exploring the relevance of practice theories for the governance of sustainable consumption practices in the new world-order. *Global Environmental Change, 21*(3), 813-822. DOI: 10.1016/j.gloenvcha.2011.03.010

Talukder, M. (2011). Development of an enhanced model of innovation adoption by individual employees. *Journal of Asia Pacific Business, 12*(4), 316–339. DOI: 10.1080/10599231.2011.591691

Tao, D., Wang, T., Wang, T., Zhang, T., Zhang, X., & Qu, X. (2020). A systematic review and meta-analysis of user acceptance of consumer-oriented health information technologies. *Computers in Human Behavior, 104,* 106147.

Thomas, D. (2018). Advanced maintenance in manufacturing: Costs and benefits. In *Annual Conference of the PHM Dociety* (pp. 24-27).

Ulring, E. (2020). How predictive maintenance improves efficiencies across five industries. *IBM*. Retrieved from https://www.ibm.com/blogs/cloud-computing/2020/01/13/predictive-maintenanceefficiencies-client-case-studies/

van de Kerkhof, R. (2020). *It's about Time: Managing Implementation Dynamics of Condition-based Maintenance*. CentER, Tilburg University. DOI: 10.26116/center-lis-2004

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. DOI: 10.2307/30036540

Vogl, G. W., Weiss, B. A., & Helu, M. (2019). A review of diagnostic and prognostic capabilities and best practices for manufacturing. *Journal of Intelligent Manufacturing*, *30*, 79-95. DOI: 10.1007/s10845-016-1228-8

Wagner, C., & Hellingrath, B. (2019). Implementing Predictive Maintenance in a company: Industry insights with expert interviews. *2019 IEEE International Conference on Prognostics and Health Management (ICPHM).* San Francisco, California, USA: Institute of Electrical and Electronics Engineers (IEEE).

Williams, Z. D., Scully, P., & Lueth, K. L. (2017). Predictive Maintenance- Market Report 2017-2022. Hamburg, Germany: IoTAnalytics GmbH.

Xu, R., Frey, R., Fleisch, E., & Ilic, A. (2016). Understanding the impact of personality traits on mobile app adoption: Insights from a large-scale field study. *Computers in Human Behavior, 62*, 244–256. DOI: 10.1016/j.chb.2016.04.011

Ye, C. (2018). *A system approach to implementation of predictive maintenance with machine* *learning*. Doctoral dissertation, Massachusetts Institute of Technology. Retrieved from https://dspace.mit.edu/handle/1721.1/118502

Zhang, T., & Nuttall, W. J. (2011). Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation. *Journal of Product Innovation Management*, *28*(2), 169-186. DOI: 10.1111/j.1540-5885.2011.00790.x

Appendices: QUESTIONNAIRE

INTRODUCTION

The objective of this research is to identify the various factors that impact the implementation of predictive maintenance within the manufacturing sector of the United Arab Emirates. Please complete the questionnaire with precision by selecting the appropriate boxes or providing responses in the designated areas. The viewpoints expressed by the participant in the survey hold significant value for the research and will be treated with the highest level of privacy. It is advised not to include personal identification on the questionnaire. Your feedback would be highly valued.

Name of the organization: ………………………………….

SECTION I: BACKGROUND INFORMATION

1. Gender

a) Male
b) Female

2. Age Bracket

a) Below 20 years
b) 20-29 years
c) 30-39 years
d) 40-49 years
e) 50 years and above

3. What is your designation in the organisation?

a) Plant/General Manager
b) Manager
c) Engineer
d) Supervisor
e) Others (specify) ………………………………………

4. Your highest level of education?

a) Certificate/Diploma
b) Degree
c) Post Graduate Degree
d) Others (specify) ……………………………………………

5. Working Experience in the Organization.

a) 1-5 years 6-10 years
b) 11-15 years
c) above 15 years

6. To what degree has this Organization implemented intelligent predictive maintenance within its operational framework? Please mark the appropriate cell that best represents the level of implementation within your organization.

Use a scale of 1- 5 where: 1 = Strongly Disagree (SD), 2 = Disagree (D), 3= Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)

STRONGLY AGREEE	**DISAGREE**	**NEUTRAL**	**AGREE**	**STONGLY AGREE**

7. To what degree has your organization been affected by the smart predictive maintenance technologies factors listed below? Please mark the appropriate cell that closely represents the level of implementation within your organization.

Use a scale of 1- 5 where: 1 = Strongly Disagree (SD), 2 = Disagree (D), 3= Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)

Predictive maintenance factors	1	2	3	4	5
• User perception factor					

• Cost reduction factor					
• Job effectiveness factor					
• Environmental factors					
• Technological factors					
• Individual factors					
• Economic factors					
• Effectiveness and efficiency					

Relative advantage refers to the extent of the added value or benefit that an organization can obtain by adopting a new technology or innovation, as opposed to maintaining the current state of affairs. The degree to which the novel technology is perceived as superior in comparison to its antecedent technology.

8. Indicate by ticking (√) the cell which closely reflects the extent to which relative advantage has influenced adoption of smart predictive maintenance in your organization.

Use a scale of 1- 5 where: 1 = Strongly Disagree (SD), 2 = Disagree (D), 3= Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)

The impact of implementing predictive maintenance strategies within the manufacturing sector.	Strongly disagree [1]	Disagree [2]	Neutral [3]	Agree [4]	Strongly agree [5]
The manufacturing industry tends to readily adopt predictive maintenance technology due to its perceived potential to increase profitability.					
The adoption of predictive maintenance technology is perceived to enhance Cost reduction for equipment spares.					
The adoption rate of predictive maintenance technology is positively					

correlated with the perception that it enhances a firm's productivity.					
The adoption rate of predictive maintenance technology is higher when it is perceived to enhance a firm's competitive advantage in the manufacturing industry.					
The adoption of predictive maintenance technology is perceived to enhance warehouse management for equipment spares.					
Predictive maintenance technology that is perceived to enhance just-in-time maintenance is easily adopted in the manufacturing industry.					
The rapid adoption of predictive maintenance technology in the manufacturing industry is attributed to its perceived ability to improve job effectiveness.					
The adoption rate of predictive maintenance technology is higher when it is perceived to result in a reduction of manufacturing costs.					
The adoption of predictive technology in the manufacturing industry is facilitated by the perception that it enhances equipment uptime.					
The adoption rate of predictive maintenance technology is higher when it is perceived to have a positive impact on extending the lifespan of equipment.					
The adoption rate of predictive maintenance technology is higher when it is perceived to result in enhanced electrical efficiency of equipment and energy conservation.					

9. Please indicate the degree to which compatibility has impacted the implementation of smart predictive maintenance in your organization by selecting the appropriate cell and placing a checkmark (√) within it.

Use a scale of 1- 5 where: 1 = Strongly Disagree (SD), 2 = Disagree (D), 3= Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)

The impact of compatibility on the implementation of intelligent predictive maintenance within the manufacturing industry.	Strongly disagree [1]	Disagree [2]	Neutral [3]	Agree [4]	Strongly agree [5]
The adoption of predictive maintenance technology in the manufacturing industry is facilitated by its perceived compatibility with existing equipment technology.					
The manufacturing industry can readily adopt predictive maintenance technology that is compatible with its existing information and communication technology infrastructure.					
The swift adoption of predictive maintenance technology in the manufacturing industry is facilitated by its compatibility with pre-existing information security systems.					
The adoption of predictive maintenance technology is facilitated when it is perceived to be compatible with the existing organizational strategy.					
The adoption rate of predictive maintenance technology is positively influenced by the perception of top management support.					
The adoption rate of predictive maintenance technology is higher when it receives support from the entire organization.					

The rate of adoption of predictive maintenance technology is positively correlated with the perceived adaptability of employees to novel technologies and changes.					
The expeditious adoption of predictive maintenance technology within an organization is contingent upon its alignment with the organization's culture and values, as perceived by its members.					
The manufacturing industry readily adopts predictive maintenance technology that involves end user participation.					
The expeditious adoption of predictive maintenance technology is facilitated by the presence of supportive policies from both business and government entities.					
The manufacturing industry has readily embraced the utilization of predictive maintenance technology, which has already been recognized and implemented.					