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Factors Affecting Adoption of Industry 4.0 predictive maintenance by manufacturing industries: Tanzania food and beverage manufacturing industries

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ABSTRACT

Industry 4.0 has increasingly become a focal point of scholarly inquiry. Nonetheless, there remains a noticeable lack of comprehensive research on the diverse and systematic factors that influence the adoption of Industry 4.0 Predictive Maintenance (PdM 4.0) in manufacturing sectors within developing regions, particularly in East Africa. This study seeks to bridge this research gap by investigating the key determinants affecting the actual implementation of PdM 4.0 in Tanzania's food and beverage manufacturing industries. To achieve this objective, a mixed-methods research design was adopted, combining both qualitative and quantitative approaches. Qualitative data were obtained through in-depth interviews with ten industry experts, while quantitative data were collected via structured questionnaires administered to 90 professionals from various manufacturing enterprises. The data were analyzed using Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), employing SPSS and SmartPLS 4 software. The analysis identified several critical factors significantly associated with the adoption of PdM 4.0, including strategic decision-making, equipment data utilization, organizational culture, perceived ease of use, perceived benefits, resource availability, external pressures, risk perceptions, and the intention to adopt. The proposed model demonstrated a satisfactory fit, with key indices such as RMSEA = 0.048, NFI = 0.91, GFI = 0.94, $\chi^2/df = 2.67$*, and p-values below 0.05. This research offers novel contributions to the understanding of PdM 4.0 adoption by highlighting the pivotal role of managerial initiatives in promoting awareness and perceived value of the technology. The findings suggest that cultivating a data-centric organizational culture, enhancing access to necessary resources, and addressing perceived risks are essential for effective implementation. It is therefore recommended that both policymakers and industry stakeholders focus on strengthening digital infrastructure, developing tailored policy frameworks, and investing in capacity-building programs to accelerate the adoption of Industry 4.0 technologies in Tanzania's manufacturing sector.*

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INTRODUCTION

By incorporating cutting-edge technologies like artificial intelligence (AI), big data analytics, and the Internet of Things (IoT) into production processes, Industry 4.0 has completely changed the manufacturing landscape. Among the various applications enabled by these advancements, predictive maintenance has gained prominence as a critical component. This approach allows manufacturers to proactively monitor equipment conditions and anticipate potential failures. By utilizing real-time data and advanced analytical algorithms, predictive maintenance facilitates timely interventions, thereby minimizing unplanned downtime, prolonging the operational lifespan of machinery, and significantly reducing maintenance-related expenses (Lee *et al*., 2015). Despite its evident advantages, the adoption of predictive maintenance within the framework of Industry 4.0 varies significantly across manufacturing industries, influenced by a multitude of factors.

Technological readiness plays a critical role in shaping the adoption of Industry 4.0 predictive maintenance. This concept refers to the extent to which an organization possesses and can integrate essential digital infrastructure such as IoT devices, data analytics platforms, and connectivity systems necessary for deploying predictive maintenance solutions. Firms with robust technological capabilities and strong data management practices are typically better positioned to implement these systems effectively (Kusiak, 2017). In contrast, organizations with limited access to advanced technologies often encounter significant obstacles, including substantial upfront investment requirements and the challenges of integrating new digital tools with legacy systems.

Organizational readiness is another key determinant influencing the successful adoption of Industry 4.0 predictive maintenance. This dimension encompasses a company's capacity and willingness to embrace technological change, which is largely shaped by organizational culture, the availability of employee training, and the presence of a coherent strategic vision. Organizations that promote continuous improvement and invest in workforce development through targeted upskilling initiatives are more likely to realize the full potential of predictive maintenance (Tortorella et al., 2020). In contrast, resistance to change, a shortage of skilled personnel, and insufficient managerial support can significantly hinder the implementation process, even when the necessary technological tools are in place.

Economic factors also play a vital role in shaping adoption decisions. The financial feasibility of predictive maintenance is often evaluated through a cost-benefit analysis, which influences both the pace and scope of implementation. Although the long-term advantages such as reduced operational downtime and lower maintenance costs are well established, the high initial costs associated with acquiring and integrating new technologies can present a major barrier for manufacturers (Frank et al., 2019). Moreover, competitive pressures and shifting market dynamics may either accelerate or constrain adoption, as firms weigh the need for innovation against financial limitations.

This study aims to identify and analyze the factors influencing the adoption of Industry 4.0 predictive maintenance within Tanzania's manufacturing sector a critical pillar of the national economy. The research intends to raise comprehensive awareness among Tanzanian manufacturing industries (TMIs) and enhance their understanding of predictive maintenance as enabled by Industry 4.0 technologies. Additionally, the findings serve as a foundation for recommending practical strategies to facilitate more accessible and effective integration of Industry 4.0 applications, ultimately supporting improved industrial performance and competitiveness.

Manufacturing industries in Tanzania

Although Tanzania's industrial sector remains relatively modest in scale, it plays a central role in the national economy, contributing approximately 8% to the country's GDP with an average annual growth rate of 4% over the past decade. The sector is largely characterized by the production of basic consumer goods, including textiles, food and beverages, chemicals, tobacco products, plastics, wood products, and metal-based items.

In recent years, industrial development has re-emerged as a central focus in national policy, particularly under the framework of the latest development agenda. Policymakers are prioritizing structural transformation aimed at shifting the economy from low productivity and limited growth to a trajectory marked by dynamic productivity, sustained income growth, and high-value industrial output.

Globally, both developed and developing economies are actively embracing a new technological paradigm under Industry 4.0. The integration of emerging technologies into industrial systems has become a focal point in discussions surrounding the Industry 4.0. This transformation, while offering substantial opportunities, also presents challenges, particularly for firms that lack the agility to adapt to rapid technological change (Bettiol et al., 2020). Enterprises that effectively harness these technological advancements can gain a significant competitive edge and improve overall performance.

Industry 4.0 is fundamentally reshaping the ways in which companies design, manufacture, and deliver products. Through technologies such as the Internet of Things (IoT), Big Data analytics, artificial intelligence, and intelligent decision-making systems, the manufacturing sector is undergoing a significant digital transformation (Parhi et al., 2022). These technologies enable real-time connectivity and data sharing across equipment and processes, thereby enhancing responsiveness to market demands, supporting product customization, and improving operational efficiency. Real-time data such as machine conditions, fault detection, and performance metrics allow firms to optimize their production and supply chain processes. Consequently, this digital shift facilitates the emergence of smart factories that utilize continuous information flow to increase productivity and streamline operations across the value chain (Compare and Baraldi, 2020; Mhlanga, 2021).

LITERATURE REVIEW

Maintenance in Manufacturing industries

Maintenance plays a critical role in industrial operations, particularly in ensuring the efficiency of equipment and monitoring wear and degradation resulting from operational use (Carnero, 2006). Within the context of the Industry 4.0, the importance of maintenance in manufacturing industries has become even more pronounced. Effective maintenance is essential not only for sustaining the intended performance of advanced technologies but also for preserving their reliability and integrity. However, maintenance management is not a standalone task it involves a coordinated set of activities closely aligned with production plans and schedules. As such, it requires systematic planning and precise decision-making to ensure that equipment is maintained in an optimal state.

Industry 4.0 predictive Maintenance (PdM 4.0)

A key element of Industry 4.0, PdM 4.0 uses machine learning, advanced data analytics, and Internet of Things (IoT) technologies to anticipate equipment problems before they happen, cutting down on maintenance expenses and downtime (Lee et al., 2018). Research has highlighted how data-driven decision-making and real-time condition monitoring can improve operational efficiency (Kumar and Galar, 2020). But while industrialized nations have made great strides in adopting PdM 4.0, developing countries especially those in Africa face a number of obstacles, such as a shortage of skilled labor, poor infrastructure, and opposition to technological change (Mourtzis et al., 2021).

Additionally, recent studies have demonstrated how PdM 4.0 can enhance sustainability in manufacturing sectors by maximizing resource use and cutting waste (Jardim-Gonçalves *et al*., 2019). Despite these benefits, adoption remains low in many Tanzanian industries due to high implementation costs and limited knowledge of advanced predictive analytics (Mburu *et al*., 2022). Addressing these barriers requires targeted policies and investments in education, training, and digital transformation initiatives to ensure successful integration of PdM 4.0 technologies in the region.

Factors influencing the adoption of Industry 4.0 predictive maintenance practices

Perceived strategic decisions (SD)

The adoption of Industry 4.0 predictive maintenance procedures in manufacturing businesses is heavily influenced by strategic decisions. The adoption and application of advanced maintenance procedures are directly impacted by organizational decisions made on technology expenditures, resource allocation, and long-term goals (Yazici, 2009). For instance, in order to improve operational efficiency and keep a competitive advantage in the market, manufacturing companies that place a high priority on innovation and competitiveness are more likely to invest in cutting-edge technologies, such as predictive maintenance systems. Similar to this, businesses may use predictive maintenance systems to lower the chance of equipment failures, cut down on unscheduled downtime, and improve maintenance schedules as a result of strategic decisions made about risk management and cost optimization. As a result, industrial companies that base their strategy choices on Industry 4.0 goals are more likely to adopt predictive maintenance practices, as these decisions reflect a proactive approach to leveraging technology for operational improvement and competitive advantage.

Hypothesis 1*: The inclination to implement PdM 4.0 is positively impacted by the perceived MI strategic decisions*

Perceived equipment data (ED)

The adoption of PdM 4.0 by the manufacturing industries is significantly influenced by perceived equipment data. This element includes how the company views the caliber, dependability, and accessibility of data pertaining to equipment. Computerized maintenance management systems (CMMS) are a common tool used by manufacturing companies to effectively gather, store, and analyze equipment data (Robatto et al., 2023). By guaranteeing prompt access to maintenance history, condition monitoring data, and real-time equipment performance indicators, the presence of a strong CMMS lays the groundwork for predictive maintenance programs. Additionally, the organization's confidence in the efficacy and dependability of predictive maintenance strategies is increased by the information guaranteed for predictive maintenance, such as sensor readings, equipment health indicators, and insights from predictive analytics. Historical information obtained from records of equipment performance and previous repair operations acts as a valuable resource for training predictive maintenance algorithms, identifying failure patterns, and optimizing maintenance schedules. Therefore, manufacturing industries with a favorable perception of equipment data availability, quality, and reliability are more likely to express intention towards adopting Industry 4.0 predictive maintenance practices, as they recognize the critical role of data-driven insights in optimizing equipment reliability, reducing downtime, and enhancing operational efficiency.

Hypothesis 2*: Perceived equipment data availability has positive influence towards adoption of industry 4 predictive maintenance*

Perceived organizational culture (OC)

Perceived managerial culture plays a pivotal role in shaping manufacturing firms' intentions to adopt Industry 4.0 predictive maintenance practices. This concept encompasses the shared beliefs, values, and norms among employees regarding innovation, technological change, and organizational adaptability (Ibidunni et al., 2013). Leadership support is particularly influential, as it sets the strategic direction and cultivates an environment that encourages the integration of new technologies. Organizations led by proactive and visionary leaders are more likely to develop a culture that prioritizes innovation, supports experimentation, and recognizes proactive problem-solving efforts.

Furthermore, organizational culture significantly affects the level of risk tolerance within a firm. Cultures that promote learning from failure and view experimentation as a path to growth tend to be more receptive to advanced technologies such as predictive maintenance. In parallel, organizational agility—defined by a firm's flexibility, responsiveness, and adaptability to changing market conditions—is equally critical for the successful adoption of Industry 4.0 initiatives. Agile organizations can more readily adjust to technological advancements and leverage predictive maintenance to improve operational efficiency and competitiveness.

In summary, manufacturing firms that exhibit a perceived organizational culture marked by strong leadership support, a high tolerance for risk, and agile decision-making processes are more likely to demonstrate a strong intention to adopt Industry 4.0 predictive maintenance. These cultural attributes create a conducive environment for continuous improvement, technological innovation, and sustained competitive advantage**.**

Hypothesis 3: *Perceived organizational culture has positive influence on industry 4.0 predictive maintenance adoption*

Perceived ease of use (PEOU) and perceived usefullness (PU)

According to Davis (1989), perceived usefulness is the degree to which an individual believes that using technology would improve the caliber of their work. Perceived utility is a key component of the Technology Acceptance Model that influences computer acceptance behavior, and its importance in technology adoption has been recognized (Liu, 2005). Furthermore, perceived utility and perceived ease of use have an impact on the intention to practice (Leong et al., 2011). What a little effort a person believes using technology will need determines how easy they believe it to be. Furthermore, one important aspect affecting the intention of manufacturing businesses to embrace Industry 4.0 predictive maintenance techniques is perceived simplicity of use.

This component includes the subjective opinions of staff members regarding the usefulness, accessibility, and friendliness of predictive maintenance systems. Users' impressions of ease of use are greatly influenced by interface design; well-designed interfaces with user-friendly features, clear information presentation, and intuitive navigation make system engagement easier. Good training programs can help employees perceive ease of use by giving them the skills and information they need to use predictive maintenance systems efficiently. Extensive training ensures that users understand how to use interfaces, interpret system outputs, and perform predictive maintenance activities. Additionally, users' confidence in their ability to resolve issues and get beyond barriers while using predictive maintenance solutions is increased by the availability of technical support channels such as online forums, help lines, and user manuals. Prompt and responsive technical support enhances users' impressions of ease of use by offering assistance and guidance when required. Thus, manufacturing sectors with favourable views of interface design, training effectiveness, and technical assistance are more likely to view predictive maintenance systems as user-friendly. Employees will feel more capable and secure when utilizing these technologies for maintenance duties, which will boost adoption intentions.

Hypothesis 4*: perceived ease of use influences adoption intention of industry 4.0 predictive maintenance*

Hypothesis 5*: Perceived usefulness has influence to adoption intention of PdM 4.0*

Perceived benefit (PB)

Industry 4.0, according to Szozda (2017), assists businesses in becoming fully automated. These businesses' cost-effectiveness is predicated on their ability to custom manufacture goods in small quantities and deliver them to clients at the lowest possible cost. However, a major factor influencing the industrial industries' intention to adopt Industry 4.0 predictive maintenance techniques is perceived benefit. This component includes the subjective opinions of staff members regarding the benefits and successful outcomes of using predictive maintenance technologies. As predictive maintenance enables proactive equipment repair, decreasing unscheduled downtime and optimizing production uptime, increased operational efficiency is a major perceived benefit. Manufacturing companies can optimize production schedules and resource efficiency by scheduling maintenance tasks during planned downtime, which is achieved by anticipating possible equipment breakdowns before they happen. Another important perceived advantage is decreased downtime, which immediately boosts profitability, customer happiness, and production output.

Furthermore, predictive maintenance enhances asset reliability by identifying and addressing potential equipment issues before they escalate into costly failures, prolonging asset lifespan and ensuring consistent performance. Cost-saving is also a prominent perceived benefit, as predictive maintenance helps reduce maintenance costs associated with reactive maintenance approaches, such as emergency repairs and production losses due to unplanned downtime. Predictive maintenance helps manufacturing companies manage resources more effectively and save total maintenance costs by streamlining maintenance plans and resource allocation. Because they understand the potential benefits to operational performance, productivity, and financial results, manufacturing industries that view increased operational efficiency, decreased downtime, improved asset reliability, and cost savings as major advantages of predictive maintenance are therefore more likely to express intention towards adopting Industry 4.0 predictive maintenance practices.

Hypothesis 6: *Perceived benefit has positive influence to adoption intention of industry 4.0 predictive maintenance*

Perceived resource availability (RA)

Perceived behavioural control is one of the motivational elements that Ajzen (1991) claims are involved in deliberate usage. The degree of ease or difficulty with which an action can be carried out, as well as whether it is restricted or regulated, are reflected in perceived behavioural control. Regarding the connection between MIs' resources and technology utilization, Nguyen and Luu (2020) pointed out that MIs need to innovate in order to employ technologies like big data because they have limited financial and human resources.

In manufacturing businesses, the intention to embrace Industry 4.0 predictive maintenance methods is heavily influenced by perceived resource availability. This component includes the subjective opinions of staff members regarding the availability and sufficiency of resources required for the installation and upkeep of predictive maintenance systems. Financial resources are essential because it can take a significant amount of money to undertake infrastructure modifications, hire staff, and purchase predictive maintenance solutions. Manufacturing companies are able to purchase predictive maintenance systems up front and set aside funds for continuous maintenance and system upgrades because they believe they have adequate financial resources. Technological infrastructure is another essential component, as it provides the foundational framework for implementing predictive maintenance solutions. Perceptions of robust technological infrastructure, including data collection sensors, communication networks, and computing systems, facilitate the seamless integration and operation of predictive maintenance tools within existing manufacturing processes. Furthermore, attitudes regarding the availability of trained persons are critical because the successful deployment of predictive maintenance depends on the availability of personnel who possess the necessary technical know-how and training to efficiently operate, maintain, and analyze data from predictive maintenance systems. Manufacturing companies can hire, develop, and retain workers who possess the requisite skills in data analytics, machine learning, and maintenance engineering, thanks to perceptions of access to competent labor. Because they see fewer obstacles to obtaining and deploying the resources required for the successful implementation and utilization of predictive maintenance systems, manufacturing industries that perceive sufficient availability of financial resources, technological infrastructure, and skilled personnel are therefore more likely to express intention towards adopting Industry 4.0 predictive maintenance practices.

Hypothesis 7*: Perceived resource availability has positive influence to adoption indentation of industry 4.0 predictive maintenance*

Perceived risk perception (RP)

The intention of manufacturing businesses to embrace Industry 4.0 predictive maintenance techniques is significantly influenced by perceived risk awareness. Employees' subjective assessments of the possible hazards and concerns related to using predictive maintenance technologies are covered by this aspect. Because industrial companies may be concerned about the efficacy and dependability of predictive maintenance systems, perceived risk of technological failure is a major problem. Adoption may be hampered by the risk of spending money on technologies that might not generate the anticipated profits or experience technical issues. Data security concerns represent another significant risk factor, as predictive maintenance relies on collecting and analyzing large volumes of sensitive equipment data. Perceptions of inadequate data security measures or vulnerabilities in predictive maintenance systems may lead to concerns about unofficial access, data breaches, and potential exposure of proprietary information. Additionally, potential disruptions to existing processes can heighten risk perceptions, as manufacturing firms may worry about the impact of implementing predictive maintenance on production workflows, supply chain operations, and overall business continuity. Concerns about integration challenges, training requirements, and resistance from employees or stakeholders can exacerbate perceptions of risk and uncertainty. Therefore, manufacturing industries with higher perceived risk perception, including concerns about technology failure, data security, and disruptions to existing processes, are less likely to express intention towards adopting Industry 4.0 predictive maintenance practices, as these perceived risks overshadow the perceived usefulness and potential benefits of predictive maintenance technologies.

Hypothesis 8*: Perceived risk perception has influence to predictive maintenance 4.0 adoption*

External pressure (EP)

The inclination of manufacturing businesses to embrace Industry 4.0 predictive maintenance techniques is significantly influenced by perceived external pressure. This component includes the subjective opinions of staff members regarding the outside factors and pressures that encourage or mandate the use of predictive maintenance. The adoption of PdM 4.0 ensures compliance with safety, environmental, or quality standards may be mandated or encouraged by industry standards and government legislation, which constitute a considerable external pressure. Perceptions of regulatory pressure can motivate manufacturing firms to adopt predictive maintenance to avoid penalties, maintain industry certifications, or secure government contracts. Competitive pressure is another key external driver, as companies may feel compelled to adopt predictive maintenance to remain competitive in the market. Perceptions of competitors adopting or investing in predictive maintenance technologies can create a sense of urgency and prompt manufacturing firms to follow suit to maintain market share, attract customers, or differentiate their offerings. Additionally, customer demands play a pivotal role in driving adoption intentions, as perceptions of increasing customer expectations for product quality, reliability, and service may push manufacturing firms to adopt predictive maintenance to meet or exceed customer requirements. Adoption can be strongly influenced externally by perceptions of consumer preferences, comments, or requests for predictive maintenance capabilities. Therefore, manufacturing industries are more likely to express intention to adopt Industry 4.0 predictive maintenance practices when they perceive increased levels of external pressure, such as regulatory requirements, competitive pressure, and customer demands. This is because they view external forces as powerful motivators for implementing predictive maintenance technologies in order to stay compliant, competitive, and customer responsive.

Hypothesis 9: *perceived external pressure has influence to adoption of industry 4.0 predictive maintenance*

Theoretical Review

This study is grounded in four well-established theoretical frameworks commonly utilized across various academic disciplines: the Theory of Planned Behavior (TPB) proposed by Ajzen (1991), the Technology Acceptance Model (TAM) developed by Davis (1989), the Combined TAM-TPB Model (C-TAM-TPB) introduced by Taylor and Todd (1995), and the Resource-Based Theory (RBT). Together, these theories offer a comprehensive lens for examining the factors for adoption of PdM 4.0 in manufacturing industries.

TPB sheds light on how subjective standards, perceived behavioral control, and individual attitudes influence behavioral intentions (Ajzen, 1991). On the other hand, TAM highlights that a technology's perceived utility and perceived ease of use are the main factors that determine its acceptance (Davis, 1989). By combining essential components of the TPB and TAM, the C-TAM-TPB model provides a stronger framework that accounts for both internal organizational attitudes and external variables like enabling circumstances and social impact (Taylor and Todd, 1995).

By combining these theoretical perspectives, the study's conceptual model ensures a balanced and systematic understanding of technology adoption. It accounts for the multifaceted nature of decision-making in manufacturing industries, where organizational culture, technological capability, and individual perceptions collectively shape the adoption of PdM 4.0.

Additionally, the Resource-Based Theory (RBT) provides insights into how firms leverage internal resources to gain competitive advantages in adopting Industry 4.0 PdM. According to RBT, organizations with superior technological, human, and financial resources are better positioned to implement predictive maintenance solutions effectively. This theory highlights the importance of strategic resource allocation and capability development in ensuring successful PdM 4.0 adoption in Tanzania’s manufacturing sector (Barney, 1991). The combination of these theories strengthens the study’s foundation and offers a robust analytical framework for assessing adoption factors.

Conceptual Framework

Figure 1 presents conceptual framework developed for this study delineates the critical factors that influence the adoption of Industry 4.0 Predictive Maintenance (PdM 4.0) within Tanzania's food and beverage manufacturing sector. This framework is theoretically anchored in four foundational models: the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the Combined TAM-TPB Model (C-TAM-TPB), and the Resource-Based Theory (RBT). By integrating these perspectives, the framework captures a multidimensional view of adoption behaviour encompassing individual attitudes, organizational capabilities, perceived technological benefits, and contextual influences thereby offering a comprehensive basis for examining PdM 4.0 implementation in the Tanzanian manufacturing context.

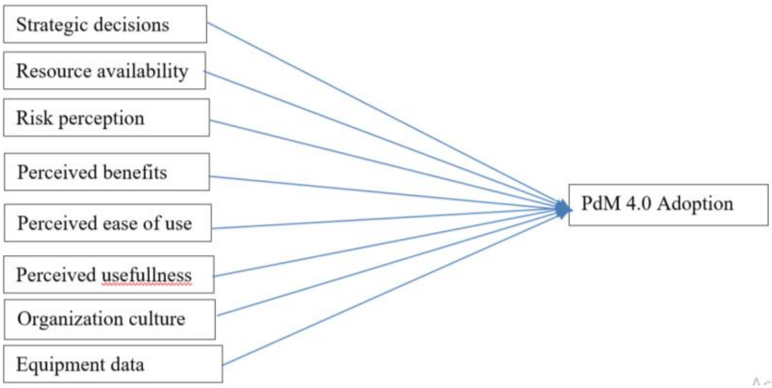

Figure 1: Conceptual framework.

The framework identifies three main categories of variables: Technological Factors, Organizational Factors, and External Factors, which collectively impact Adoption Intention and ultimately lead to the Actual Adoption of PdM 4.0.

METHODS AND MATERIALS

Study Approach

This study adopted a mixed-methods approach, both qualitative and quantitative research techniques were used to provide a comprehensive assessment of the adoption of Industry 4.0 Predictive Maintenance (PdM 4.0) within Tanzanian manufacturing industries. The use of this integrated approach ensures a well-rounded understanding by merging in-depth insights gained from expert interviews with statistical validation derived from survey data. Given the complexity of the relationships between various influencing factors and the adoption of PdM 4.0, Structural Equation Modelling (SEM) is employed as the primary analytical technique to assess these interactions. SEM was chosen for the following reasons:

- It enables the examination of multiple relationships simultaneously, capturing both direct and indirect effects among variables.
- It allows for measurement errors to be incorporated into the analysis, improving model accuracy.
- SEM is suitable for testing theoretical models that involve latent variables, which are measured through multiple observed indicators.

Measurement Model

Before assessing the structural links, the measuring model for this study was created to assess the validity and reliability of the latent components. A number of statistical techniques were used to evaluate these attributes. Internal Uniformity Cronbach's Alpha (CA) and Composite Reliability (CR) were used to assess reliability; values above 0.7 were deemed acceptable. Average Variance Extracted (AVE) was used to test convergent validity; a value higher than 0.5 denotes that each concept explains a sufficient amount of variance. The Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker Criterion were used to evaluate discriminant validity, making sure that each construct in the model is unique and not highly linked with the others.

Structural Model

The suggested hypotheses were tested and the correlations between the variables were examined by analyzing the structural model once the measurement model had been validated. The structural model's evaluation criteria comprised a number of important metrics:

Model Fit Indices

An adequate fit is indicated by a Root Mean Square Error of Approximation (RMSEA) value less than 0.08. The Normed Fit Index (NFI) and the Goodness of Fit Index (GFI): Values greater than 0.90 indicate a good fit. A well-fitting model is indicated by a chi-square to degrees of freedom ratio (X^2/df) of less than 3.0. The route Coefficients (β): With statistical significance taken into account at $p < 0.05$, these coefficients were used to evaluate the direction and strength of correlations between variables. Higher R2 values indicate better prediction ability. R2 values indicated the model's explanatory power.
Additionally, ten experts were interviewed in-depth to refine and modify the conceptual model's variables and measurement items. To ensure that the experts were representative of the manufacturing sector, participants were carefully selected based on their relevant experience and industry knowledge. The interviews provided comprehensive and diverse insights into the research topic. After posing pre-selected questions, participants were also given recommendations regarding the measurement items to further enhance the model. A thorough interviewing technique was used to assess the initial conceptual model, which had eight variables and twenty-six measuring items created from the theoretical foundation. The results from the in-depth interviews indicated the necessity of removing five measurement items from the model: PB5, TR4, RA4, OC2, and EP3.

Quantitative Research

Descriptive Analysis

This study surveyed 15 manufacturing industries (MIs) and collected 90 valid questionnaires, resulting in a response rate of 95.42% (with 4 questionnaires deemed invalid). Six limited corporations (58.08%), four joint-stock companies (23.74%), five private enterprises (11.36%), and two other company types (6.82%) were included in the sample. According to the findings, 84.34% of MIs had implemented the three essential Industry 4.0 technology pillars: cybersecurity, big data and analytics, and cloud computing. In particular, 64.90% of MIs had incorporated big data and analytics into their operations, 74.50% had put cybersecurity measures in place, and 70.71% had embraced cloud technology.

Explorative factor analysis

Exploratory Factor Analysis (EFA) was used to refine the measurement items, and items that did not fit well were eliminated. Principal Factor Analysis with Varimax Kaiser normalization rotation was used as the extraction method, and items PEOU5, RP1, and OC3 were eliminated because their factor loadings were less than 0.5, while the remaining measurement items were kept because their factor loadings were greater than 0.5 (Hair et al., 1995). The Kaiser-Meyer-Olkin (KMO) value for sampling adequacy was 0.889, and Bartlett's Test of Sphericity produced a Chi-Square value of 1318.983 (df = 1286; p 0.000), indicating that the data were suitable for factor analysis. The cumulative extraction sum of squared loadings was 62.154%, showing a satisfactory level of explained variance. The statistically significant and sufficiently high factor loadings for each construct demonstrated the acceptance of the indicators and their corresponding constructs, and the conceptual model, comprising eight components and twenty-four measurement items, was judged suitable for testing using Structural Equation Modeling (SEM).

Structural Equation Modeling (SEM)

When testing complicated models without mediated-moderation interactions, Partial Least Squares Structural Equation Modeling

(PLS-SEM) is a suitable method. One of the best SEM tools, SmartPLS 4, makes the Covariance-Based SEM (CB-SEM) estimate procedure easier. According to the findings, the model kept eight components out of the twenty-four measurement items that were judged adequate for additional evaluation (Figure 2).

Regarding model fit, the results indicated excellent approximations of goodness of fit. The Standardized Root Mean Square Residual (SRMR) for the estimated model was 0.073, and for the saturated model, it was 0.060, both of which comply with the acceptable threshold of 0.08 (Çakıt et al., 2020). These values suggest that the model fits well overall, and no measurement error links were found, ensuring the one-dimensionality of the model and consistency in the measurement items.

Additionally in Table 1, Variance Inflation Factor (VIF) values for the formative indicators were used to assess the collinearity of the indicators. The VIF values ranged from a minimum of 1.455 for RA4 to a maximum of 4.092 for TR3. As all VIF values remained well below the 5.0 threshold, we can confidently conclude that collinearity between the predictor constructs in the structural model is not a significant concern.

Table 1: Value inflation Factor -Collinearity test

Collinearity statistics (VIF) – Inner model – List	
	VIF
Adoption intention -> Actual adoption	1.239
Equipment data -> Adoption intention	1.003
External pressure -> Perceived usefulness	1.214
Organizational culture ->Perceived usefulness	1.025
Perceived benefit -> Adoption intention	1.225
Perceived usefulness -> Actual adoption	1.239
Risk perception -> Perceived usefulness	1.223
Strategic decision -> Adoption intention	1.228

Valuation of the Measurement Model

Individual reliability (factor loadings and communalities) and internal consistency (composite reliability, convergent validity via Average Variance Extracted [AVE], and discriminant validity via the Heterotrait–Monotrait [HTMT] ratio) were carefully examined in order to evaluate the data's validity and reliability.

Table 2: Discriminant validity

Discriminant validity via Heterotrait–Monotrait ratio						
	Actual adoption	Adoption intention	Equipment data	External pressure	Organizational culture	Perceived benefit
Actual adoption						
Adoption intention	0.644					
Equipment data	0.094	0.107				
External pressure	0.635	0.891	0.075			
Organizational culture	0.075	0.097	0.512	0.125		
Perceived benefit	0.431	0.657	0.378	0.424	0.511	
Perceived usefulness	0.963	0.555	0.103	0.646	0.083	0.414
Risk perception	0.579	1.155	0.099	0.521	0.150	0.994
Strategic decision	0.638	0.878	0.082	1.098	0.127	0.424

Internal Consistency Reliability

Sarstedt et al. (2017) state that if a factor's Composite Reliability, Cronbach's Alpha, and Rho-A values are all higher than 0.7, it is considered reliable. The findings showed that the Composite Reliability for all of the study's constructs ranged from 0.873 to 0.928, the Cronbach's Alpha coefficients ranged from 0.783 to 0.904, and the Rho-A values ranged from 0.783 to 0.915 (see Table 3). These findings support the measurement model's high level of internal reliability.

This study used Average Variance Extracted (AVE), Indicator Reliability, and Loadings to evaluate Construct Validity. With indicator reliability for 13 measurement items ranging from 0.716 to 0.924, all of which exceeded the acceptable criterion of 0.750, the results showed that the outer loadings of the 24 measurement items were good. All eight constructions had AVE values over the 0.5 cutoff, ranging from 0.623 (PEOU) to 0.708 (PB). Consequently, six constructs were deemed to have attained validity (refer to Table 3).

Convergent Validity

Table 3: Convergent validity

Construct reliability and validity - Overview				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
Actual adoption	0.915	0.923	0.940	0.796
Adoption intention	0.634	0.731	0.776	0.486
Equipment data	0.856	-0.814	0.662	0.369
External pressure	0.904	0.923	0.933	0.776
Organizational culture	0.917	0.718	0.913	0.726
Perceived benefit	0.279	0.205	0.396	0.273
Perceived usefulness	0.905	0.914	0.934	0.779
Risk perception	0.673	0.624	0.761	0.445
Strategic decision	0.902	0.917	0.932	0.775

Discriminant Validity

The Heterotrait-Monotrait (HTMT) ratio was used in this study to evaluate the components' discriminant validity. The findings showed that every construct had respectable HTMT values, with 0.653 being the highest. Discriminant validity was verified because all values fell below the suggested cutoff of 0.75 (see to Tables 3 and 4).

In terms of explanatory power, the three endogenous constructs of PdM 4.0—Organizational Culture (OC), Resource Availability (RA), and Actual Adoption (AA)—had R2 values of 0.552, 0.459, and 0.350, respectively, as shown in Figure 2. According to these results, the model accounts for roughly 53.2% of the variation in the real-world implementation of Industry 4.0 Predictive Maintenance. The structural model and its predictive relevance are well supported by this degree of explanatory power.

Predictive Relevance (Q2): For all three endogenous constructs, the Q2 values, which are used to evaluate the predictive relevance of the model through cross-validated redundancy, were significantly above zero. In particular, the highest Q2 score was 0.334 for perceived advantage (PA), 0.289 for perceived benefit (PB), and 0.312 for actual adoption of PdM 4.0. Established benchmarks state that predictive significance is indicated by Q2 values larger than zero (Hair et al., 2019). Strong proof that the model has sufficient predictive accuracy for the endogenous latent components can be found in these results (see Table 5).

Table 4: Heterotrait–Monotrait ratio (HTMT) - Matrix

Discriminant validity - Heterotrait–Monotrait ratio (HTMT) - Matrix						
	Actual adoption	Adoption intention	Equipment data	External pressure	Organizational culture	Perceived benefit
Actual adoption						
Adoption intention	0.644					
Equipment data	0.094	0.107				
External pressure	0.635	0.891	0.075			
Organizational culture	0.075	0.097	0.512	0.125		
Perceived benefit	0.431	0.657	0.378	0.424	0.511	
Perceived usefulness	0.963	0.555	0.103	0.646	0.083	0.414
Risk perception	0.579	1.155	0.099	0.521	0.150	0.994
Strategic decision	0.638	0.878	0.082	1.098	0.127	0.424

Table 5: Construct reliability

Construct reliability and validity - Overview				
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
Actual adoption	0.915	0.923	0.940	0.796
Adoption intention	0.634	0.731	0.776	0.486
Equipment data	0.856	-0.814	0.662	0.369
External pressure	0.904	0.923	0.933	0.776
Organizational culture	0.917	0.718	0.913	0.726
Perceived benefit	0.279	0.205	0.396	0.273
Perceived usefulness	0.905	0.914	0.934	0.779

Risk perception	0.673	0.624	0.761	0.445
Strategic decision	0.902	0.917	0.932	0.775

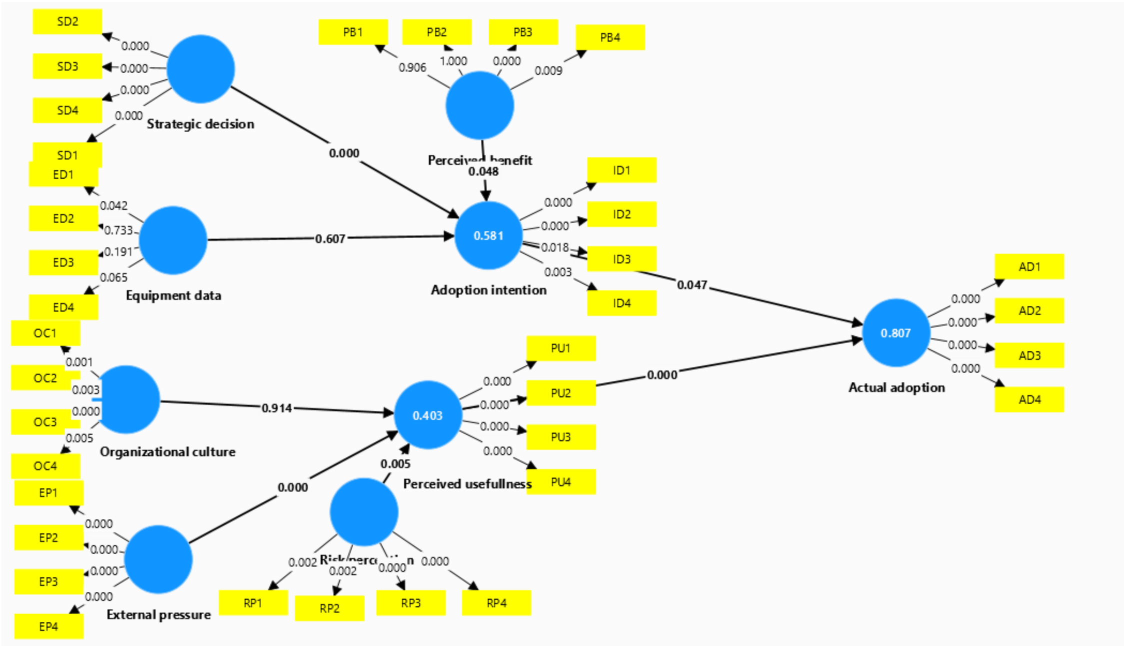

Figure 1: Structure equation model

Table 6: Path coefficients

Path coefficients – Mean, STDEV, T value, p values					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Adoption intention -> Actual adoption	0.131	0.138	0.066	1.988	0.047
Equipment data -> Adoption intention	-0.046	-0.032	0.090	0.514	0.607
External pressure -> Perceived usefulness	0.495	0.482	0.073	6.754	0.000
Organizational culture ->Perceived usefulness	-0.011	-0.010	0.106	0.108	0.914
Perceived benefit -> Adoption intention	0.208	0.226	0.105	0.976	0.048
Perceived usefulness -> Actual adoption	0.833	0.827	0.052	16.148	0.000
Risk perception -> Perceived usefulness	0.239	0.259	0.085	2.794	0.005
Strategic decision -> Adoption intention	0.645	0.641	0.109	5.929	0.000

Hypotheses Testing

The bootstrapping approach was used to assess the conceptual model and its eight assumptions. The bulk of the proposed correlations were statistically supported, according to the data (see Table 7), which validated the model's suitability. With route coefficients ranging from 0.14 to 0.52, seven of the eight hypotheses showed significance at the $p < 0.05$ level (see Figure 2). However, because Hypothesis H7 did not reach the statistical significance criterion, it was not supported. Overall, these results corroborate the suggested model's robustness, with six hypotheses receiving complete support and one (H7) receiving no support.

Table 7: Hypothesis Test

Constructs	Coefficients	P-values	Hypothesis Test	
ED>PU	0.402	0.000		Supported
OC>PB	0.263	0.001		Supported
PB>AD	0.552	0.002		Supported
PEOU>AD	0.154	0.001		Supported
PU>AD	0.126	0.001		Supported
RA>PU	0.234	0.090		Not supported
RP>PU	0.392	0.002		Supported
SD>PB	0.231	0.001		Supported

Discussion

The results of this study show that the actual adoption of Industry 4.0 Predictive Maintenance (PdM 4.0) is significantly positively impacted by adoption intention ($\beta = 0.131$, $p = 0.047$). This is consistent with the central claims of the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM), which both identify behavioral intention as the main predictor of actual technology usage (Davis, 1989; Ajzen, 1991). These results are consistent with earlier studies by Masood and Sonntag (2021) and Wang et al. (2020), which found that companies with a strong digital commitment are more likely to successfully adopt emerging technologies.

Additionally, a highly significant factor of actual adoption was perceived usefulness ($\beta = 0.833$, $p = 0.000$), highlighting the significance of perceived technological benefits in promoting PdM 4.0 integration. This result is consistent with the findings of Müller et al. (2018), who found that manufacturing companies are more likely to use predictive maintenance solutions when there are obvious operational advantages, such reduced downtime and cost effectiveness.

Corporate culture, on the other hand, was shown to have a negligible impact on perceived usefulness ($\beta = -0.011$, $p = 0.914$). This finding runs counter to previous research by Ghobakhloo and Ching (2019), who revealed that a supportive corporate culture was a major factor in the adoption of Industry 4.0. This discrepancy could be explained by contextual differences; in particular, many Tanzanian manufacturing companies might not have reached the cultural maturity required to acknowledge and reaffirm the perceived advantages of predictive maintenance technologies because they are still in the early phases of digital transformation.

This study also found that strategic decision-making has a strong positive impact on adoption intention ($\beta = 0.645$, $p = 0.000$), which is consistent with Kamble et al. (2018)'s work that emphasized the importance of leadership commitment and strategic vision in promoting the adoption of Industry 4.0 technologies. On the other hand, equipment data had a negligible impact on adoption intention ($\beta = -0.046$, $p = 0.607$), suggesting that access to machine-generated data alone does not always translate into a greater desire to adopt predictive maintenance. This finding differs from Lee et al. (2020), who found that the availability of high-quality sensor data improves adoption outcomes.

A plausible explanation for this discrepancy lies in the contextual limitations within the Tanzanian manufacturing sector. Many firms may lack the advanced data analytics infrastructure and technical expertise required to process and derive value from equipment data, thereby limiting its perceived utility. These insights underscore the importance of managerial initiatives aimed at building internal analytical capabilities and fostering a clearer understanding of the strategic benefits of Industry 4.0 technologies. Addressing these contextual barriers is essential for improving adoption outcomes in developing economies.

Manufacturing industries in Tanzania are increasingly motivated to harness the potential of emerging technologies to drive innovation and improve operational efficiency. The study confirms that adoption intention significantly influences the actual adoption of Industry 4.0 predictive maintenance (PdM 4.0) within Tanzanian manufacturing industries (TMI), a finding that is consistent with existing literature. Several factors demonstrate a strong relationship with perceived usefulness, which, in turn, enhances maintenance performance. These benefits include improved machine uptime (Kearns and Sabherwal, 2006), reduced costs associated with spare parts inventory (Ibidunni et al., 2013), and increased overall productivity (Sargent et al., 2012; Waly and Thabet, 2003; Ribas et al., 2019). These outcomes reinforce the strategic importance of PdM 4.0 in achieving higher efficiency and cost-effectiveness in the manufacturing sector.

CONCLUSION AND RECOMMENDATION

This study offers valuable intuitions into the factors influencing the adoption of Industry 4.0 Predictive Maintenance (PdM 4.0) within Tanzanian food and beverage manufacturing industries. The findings underscore the pivotal role of perceived usefulness in driving actual adoption, highlighting the need for clearly demonstrating the tangible benefits of PdM 4.0 to potential adopters. Additionally, strategic decision-making and external pressure were found to significantly influence both adoption intention and perceived usefulness, indicating that top management commitment and competitive or regulatory dynamics are critical enablers in the adoption process.

Unexpectedly, organizational culture and equipment data availability did not have a significant impact on adoption intention. This suggests that challenges related to digital readiness, such as insufficient data analytics capabilities and limited workforce expertise, may hinder the effective implementation of PdM 4.0. Although firms may recognize the strategic value of predictive maintenance technologies, technical and resource-related constraints continue to pose substantial barriers to their widespread adoption. Therefore, policymakers and industry leaders should prioritize capacity building, workforce training, and infrastructure development to create an enabling environment for the adoption of Industry 4.0 Predictive Maintenance (PdM 4.0). To accelerate adoption, it is recommended that firms invest in leadership-driven digital transformation strategies, foster cross-sector collaborations for technology transfer, and improve perceived ease of use through targeted awareness and education initiatives.

Future research should investigate sector-specific adoption barriers and employ longitudinal designs to track implementation progress and long-term outcomes. By proactively addressing these critical factors, the Tanzanian manufacturing sector can fully leverage the capabilities of Industry 4.0 technologies leading to enhanced operational efficiency, minimized equipment downtime, and improved global competitiveness.

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