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Original Article

An ICT-Integrated Predictive Maintenance Model for Enhancing Plant Availability in Thermal Power Plants: A Case Study of TANESCO, Tanzania

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ABSTRACT

The thermal power sector in Tanzania faces increasing operational complexities and maintenance challenges that undermine plant reliability and efficiency. This paper focuses on the TANESCO Ubungo II Gas Plant, where recurring issues highlight the urgent need for advanced and sustainable maintenance strategies. The paper proposes a predictive maintenance model that integrates Process Control System 7 (PCS 7) with a Computerised Maintenance Management System. A mixed-methods approach was employed, combining qualitative insights from literature and field studies with quantitative techniques, including regression analysis. Key variables influencing plant availability, uptime, downtime, overhaul frequency, operational expertise, and environmental conditions were analysed using multiple regression and the Relative Importance Index to determine their relative contribution to plant performance. The findings indicate that strategic integration of ICT within maintenance frameworks significantly improves the accuracy of failure prediction, reduces downtime, and enhances operational efficiency. The model demonstrates the potential to optimise maintenance schedules, extend asset life, and lower overall operational costs. This paper contributes to the growing body of knowledge on predictive maintenance in the energy sector and provides practical insights for enhancing power plant performance in Tanzania and other developing economies.

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INTRODUCTION

Thermal power plants play a critical role in meeting the growing demand for electricity worldwide. Globally, utilities face challenges in ensuring continuous plant availability due to equipment failures, high maintenance costs, and inefficient maintenance practices. To address these issues, predictive maintenance systems, particularly those enhanced with Information and Communication Technologies (ICT), have been widely adopted [1]. These systems have demonstrated significant potential in reducing downtime, optimising maintenance schedules, and improving overall plant performance.

In Africa, the situation is even more pressing. Many countries face frequent power shortages and unreliable supply, partly due to the limited adoption of advanced maintenance technologies in thermal power plants. The lack of predictive maintenance frameworks, coupled with ageing infrastructure and financial constraints, often leads to reduced efficiency and unexpected plant outages. As a result, electricity supply remains inconsistent, hindering socio-economic development across the region.

In Tanzania, thermal power plants managed by the Tanzania Electric Supply Company (TANESCO) continue to encounter maintenance-related challenges [2]. For example, the Ubungo II Gas Plant, a major contributor to the national grid, experiences frequent equipment breakdowns linked to reactive and inconsistent maintenance practices. The absence of ICT-driven predictive maintenance systems exacerbates these challenges, leading to reduced plant availability, operational inefficiencies, and increased maintenance costs.

Despite the proven effectiveness of predictive maintenance systems globally, there is limited integration of ICT-based predictive maintenance solutions in Tanzania's thermal power plants. This gap has contributed to recurrent equipment failures and power supply interruptions.

While existing research has explored predictive maintenance in developed contexts, little attention has been given to the African and Tanzanian environments, where infrastructural, technological, and economic realities differ significantly.

This paper aims to develop an ICT-integrated predictive maintenance model to enhance plant availability in thermal power plants, with a focus on TANESCO's Ubungo II Gas Plant. By leveraging advanced artificial intelligence (AI) techniques, including machine learning, deep learning, and data analytics, the proposed model seeks to reduce downtime, optimise maintenance strategies, and enhance the reliability of electricity generation.

LITERATURE REVIEW

The SGT-800 is a dual-fuel gas turbine with a single shaft, intended for industrial power generation, offering a power output that ranges from 47 to 57 MW [4]. This technology showcases cutting-edge combustion engineering that is specifically fine-tuned for natural gas and light liquid fuels, boasting

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low emission levels and exceptional operational flexibility, making it suitable for both base load and cycling applications. The SGT-800 uses advanced materials and cooling methods to achieve impressive thermal efficiency while ensuring reliability in challenging everyday operational conditions [5].

General Packet Radio Service (GPRS) is a mobile data standard that operates on a packet-oriented basis, allowing wireless communication for industrial monitoring and control systems in power generation facilities. Within the realm of thermal power plant operations, GPRS technology supports remote monitoring capability, data exchange, and communication between the plant's control systems and external monitoring hubs. GPRS offers crucial network connectivity for systems designed to acquire real-time data, allowing for the ongoing observation of equipment performance and operational metrics of the plant [6].

Knight et al. 2024 indicate that the PCS 7 is part of the SIMATIC family and is built on Totally Integrated Automation (TIA) Siemens' philosophy for unified, seamless integration of all automation components [7].

The Siemens' Distributed Control System (DCS) is designed specifically for process automation across industries such as chemical, pharmaceutical, oil & gas, water treatment, power, food & beverage [8].

The PCS 7 is not like PLCs that are often used in discrete manufacturing, DCS systems and batch processes, where stability, scalability, and integration are very critical.

Purposive sampling will be employed to select participants who possess relevant knowledge and experience in ICT integration and predictive maintenance within thermal power plants [9]. The sampling technique ensures that the data collected is rich, relevant, and representative of the research population. The inherent availability of critical components has a significant impact on plant availability performance.

Modern thermal power plants incorporate redundant systems for critical components such as boiler feed pumps, induced draft fans, and control systems to minimise single points of failure. Equipment design factors, such as material selection, corrosion allowances, and fatigue life calculations, directly influence the mean time between failures (MTBF). According to [10], plants with N+1 redundancy configurations for critical subsystems demonstrate 8% to 12% higher availability rates compared to those with minimal redundancy.

Fuel characteristics represent a critical technical factor affecting boiler performance and availability. Variations in coal properties such as calorific value, moisture content, ash content, and sulfur levels directly impact slagging, fouling, and erosion rates in boiler pressure parts. Haghighat et al [11] established that a 5% increase in ash content leads to a 7% increase in forced outage hours related to boiler tube failures. Consistency of supply quality presents ongoing challenges for plant operators attempting to optimise combustion parameters.

The gas supply system features a complex pressure reduction process where natural gas at 50 bar is carefully regulated down to 29 bar before turbine injection. The system ensures optimal fuel delivery and maintains consistent combustion and turbine performance. Precise control during pressure reduction is essential to prevent fluctuations that could negatively impact combustion stability, turbine efficiency, and emissions. Research shows that pressure changes over ±2% of the target can lead to combustion issues, higher NOx emissions, and lower turbine availability [12].

The natural gas composition, particularly methane content, higher hydrocarbons, and inert gases, significantly influences combustion characteristics and turbine performance. Methane content typically ranges from 85-95%, with variations affecting

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heating value, flame temperature, and combustion velocity [13]. Higher heating values between 35-40MJ/m³ provide optimal turbine performance, while lower values require combustion system adjustments to maintain design output and efficiency. Research indicates that heating value variations exceeding 5% from design specifications can reduce turbine efficiency by 2-3% and increase maintenance requirements due to altered combustion dynamics [14].

Original design specifications and technology are no longer used, significantly influencing the availability performance throughout the plant lifecycle. Modern plants incorporating advanced materials, superior thermal cycle designs, and enhanced control architectures demonstrate inherently higher availability. According to [15], plants operating beyond their design lifetime (typically 25-30 years) experience an average 0.8% annual degradation in availability unless comprehensive life extension programs address critical component replacements and technological upgrades are performed.

Transmission system availability and grid frequency regulation capability constitute external technical factors affecting plant availability. Plants operating in unstable grid environments experience higher rates of protective trips and increased thermal cycling due to system disturbances. The TANESCO Ubungo II Gas Plant operates with an 11kV generation voltage that is stepped up through transformers to connect with the national grid at 132kV and 220kV transmission levels, requiring sophisticated synchronisation and protection systems to maintain stable interconnection [16]. Grid frequency variations beyond ±0.5Hz from the nominal 50Hz standard can trigger protective relays and force plant disconnection, while voltage fluctuations exceeding ±5% at the 132kV and 220kV interconnection points can compromise equipment protection and operational stability [17]. During grid disturbances, the plant's landing capability allows continued operation in isolated mode by disconnecting from the transmission network and serving local loads through the 11kV distribution system, though this requires precise frequency and voltage control to maintain stable operation within acceptable parameters of 49.5-50.5Hz and ±10% voltage tolerance [18,19]. The plant's ability to operate in island mode provides critical backup power capability during transmission system outages, but requires advanced control systems to manage load-generation balance and maintain frequency stability without external grid support. Research shows that plants operating in regions with frequent grid disturbances experience up to 15% higher trip rates and an 8% reduction in annual availability compared to identical units connected to more stable transmission networks, with voltage and frequency excursions at high transmission voltages (132kV and 220kV) causing more severe impacts than disturbances at lower distribution levels [16]. Modern grid interconnection systems incorporate advanced protection schemes, power quality monitoring, and rapid islanding capabilities that enable plants to maintain operation during grid disturbances while providing grid support services, including frequency regulation, voltage control, and reactive power compensation through sophisticated 11kV to 220kV interface systems [19].

The ambient temperature impacts, seasonal variations, and extreme weather resilience constitute environmental technical factors affecting plant availability. Also the cooling system performance, combustion efficiency, and auxiliary system availability all demonstrate sensitivity to ambient conditions. The tropical climate, where ambient temperatures typically range from 24°C to 32°C, with humidity levels fluctuating between 60% to 85% throughout the year, significantly affects gas turbine performance and auxiliary system efficiency [20]. The high ambient temperatures reduce gas turbine output by approximately 0.5-0.7% per degree Celsius above design conditions (typically 15°C), while elevated

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humidity levels above 70% can decrease combustion efficiency and increase compressor work requirements, leading to reduced plant output and efficiency. Air filtration systems become critical under these conditions, as high humidity combined with dust and salt particles from the coastal environment can clog intake filters more rapidly, requiring frequent maintenance cycles and potentially forcing output reductions when filter differential pressure exceeds design limits. However, during the dry season (June-September), lower humidity levels (50-65%) improve combustion efficiency but increase dust loading on filtration systems, while the wet season (October-May) brings higher humidity (75-85%) that can cause moisture ingestion issues and corrosion concerns for turbine components. Extreme weather events, including tropical storms, heavy rainfall, and temperature spikes, can force immediate plant shutdowns due to equipment protection requirements, with lightning strikes, flooding risks, and high winds posing additional operational challenges that require robust weather monitoring and protection systems. According to research, extreme weather events now account for approximately 7% of all forced outage hours across the thermal generation fleet, with increasing frequency and severity observed over the past decade, making weather resilience and adaptive operational strategies essential for maintaining high availability in tropical climates where temperature, humidity, and filtration challenges combine to create complex operational environments.

Predictive Maintenance and ICT Integration

Preventive maintenance represents a systematic approach to equipment upkeep performed at predetermined intervals based on equipment specifications, manufacturer recommendations, and operational experience. The maintenance philosophy aims to prevent equipment failures through scheduled inspections, component replacements, and system overhauls before deterioration reaches critical levels [21]. In thermal power plants, preventive maintenance encompasses routine activities such as boiler tube inspections, turbine blade cleaning, bearing lubrication, and control system calibrations. Research demonstrates that well-executed preventive maintenance programs can reduce unplanned outages by 35% and extend equipment life cycles by 20-30% compared to reactive maintenance approaches [22]. Nevertheless, the effectiveness of preventive maintenance depends heavily on optimising scheduling frequency, as excessive maintenance can increase costs and potential human errors, while insufficient maintenance may fail to prevent deterioration-related failures.

The predictive maintenance utilises advanced monitoring technologies, data analytics, and condition assessment techniques to predict equipment failures before they occur, enabling optimal maintenance timing based on actual equipment condition rather than predetermined schedules. This approach leverages sensors, vibration analysis, thermal imaging, oil analysis, and other diagnostic technologies to continuously monitor equipment health and performance trends. In thermal power plants, predictive maintenance applications include turbine vibration monitoring, boiler tube thickness measurements, transformer dissolved gas analysis, and generator rotor bar testing. The success of predictive maintenance depends on sophisticated data collection systems, advanced analytics capabilities, and skilled personnel capable of interpreting diagnostic information and making informed maintenance decisions.

PCC7, SCADA, DCS and Control System Technology

The simulation was carried out using MATLAB R2024b to implement a multiple linear regression model. The data used were compiled and merged into a file consisting of 36 monthly records collected from Ubungo II Gas Plant between January 2022 to December 2024. Thirty-six (36) consecutive

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months of observations (Jan 2022 – Dec 2024) were used for simulation purposes as indicated below;

- **PCS 7 Process logs** Weather and environmental Conditions are exported from PCS 7, confirming an **ICT data usage** in the predictor matrix.
- **SCADA Logs** Provided monthly metrics for Operational Expertise, Overhaul Quality & Frequency, Operating Regime, Maintenance Strategy, and Equipment Quality & Availability.
- **Plant Performance Ledger** Supplied uptime/downtime hours for the dependent variable calculation.

The simulation for predictive maintenance was based on the following;

i. Regression model equation;

$$A=\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3$$

$$+\beta_4 X_4+\beta_5 X_5+\beta_6 X_6+\varepsilon$$

(1)

ii. A= Predicted Plant Availability (%)

- X1X_1 = Weather and Environmental Conditions (from PCS 7 – ICT-embedded)
- X2X_2 = Operational Expertise
- X3X_3 = Overhaul Quality and Frequency
- X4X_4 = Operating Regime
- X5X_5 = Maintenance Strategy
- X6X_6 = Equipment Quality and Availability
- ε= Error term (unexplained variance)

Technical Factors Influencing Plant Availability

In order to validate the regression model, several diagnostic tests were conducted using MATLAB:

- **Residual Analysis:** A plot of residuals versus fitted values was generated to evaluate assumptions of linearity and homoscedasticity. The plot showed no evident patterns, suggesting that these assumptions were reasonably satisfied.
- **Normality Testing:** The Shapiro–Wilk test was applied to the residuals, and the results confirmed that they follow a normal distribution, thereby supporting the normality assumption.
- **Multicollinearity Check:** Variance Inflation Factor (VIF) values were computed for all predictors. All VIF values were found to be below three (3), indicating the absence of multicollinearity problems among the independent variables.

Table 1: Testing Statistical Results

Predictor	β-Estimate	*p*-value	Interpretation
Intercept	8.892	0.558	Baseline availability
Weather (PCS 7)	2.364	0.369	ICT-sourced; modest, not sig.
Operational Expertise	1.411	0.437	Not sig. at 5 %
Overhaul Quality & Freq.	–0.186	0.490	Negative but not sig.
Operating Regime	3.543	0.735	Not sig.
Maintenance Strategy	**7.215**	**0.064**	**Near-significant; practice lever**
Equipment Quality & Avail.	**4.477**	**0.019**	**Significant driver**

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i. **$R^2 = 0.54$ (54 % variance explained).**

ii. **MAPE = 7.81 % (< 10 % threshold for engineering accuracy).**

Based on the fitted regression model using 36 months of operational data from TANESCO Ubungo II Gas Plant, the predicted average plant availability is computed as follows:

$A = 8.892 + 2.364X1 + 1.411X2 - 0.186X3 +$

$3.543X4 + 7.215X5 + 4.477X6A =$

$8.892 + 2.364X_1 + 1.411X_2 - 0.186X_3$

$+3.543X_4 + 7.215X_5 + 4.477X_6A =$

$8.892 + 2.364X1 \quad + 1.411X2 \quad - 0.186X3$

$+3.543X4 \quad +7.215X5 \quad +4.477X6$

(2)

By using the complete dataset from 2022 to 2024, the model forecasted an average monthly plant availability as indicated in Eqn (3)

$$Aavg \approx 89.25\% \tag{3}$$

Aavg=Average

This value closely matches the actual historical mean (89.23%), with a Mean Absolute Percentage Error (MAPE) of 7.81%, indicating the model is both accurate and reliable for predictive maintenance planning. The predicted availability values ranged between 66.93% and 101.75%, with higher-end predictions occurring during months of optimal performance and maintenance conditions.

Table 2: Plant Availability

Metric	Value
Predicted Mean Availability	**89.25%**
Observed Mean Availability	89.23%
MAPE	7.81%
Predicted Min	66.93%
Predicted Max	101.75%

These results confirm that the ICT-based integration model can effectively estimate the availability of the thermal power plant using identified technical predictors, as indicated in Table 2.

Figure 1: The Residuals Plotted against the Fitted Values of the Availability Predictions.

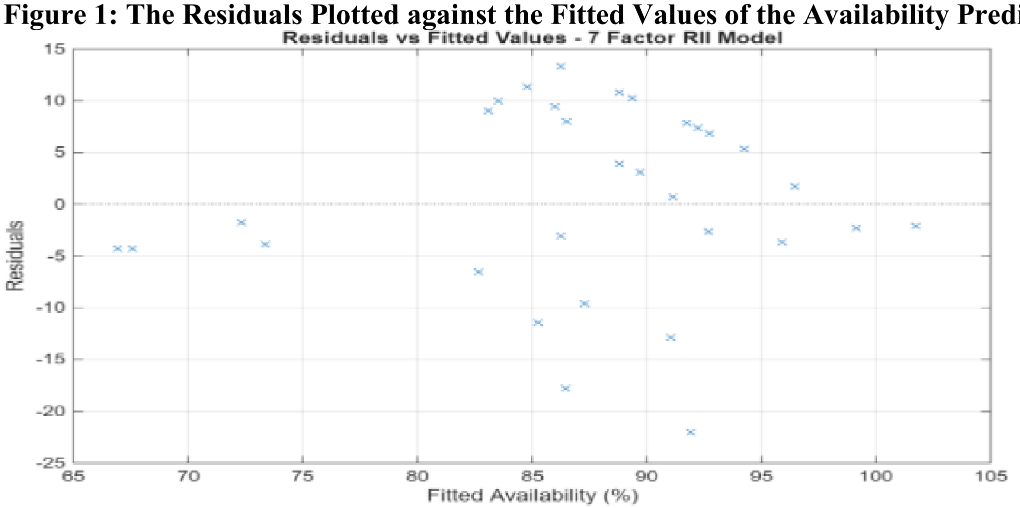

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Figure 1 shows that the residuals are randomly scattered around zero, with no discernible pattern or funnel shape. This indicates that the model satisfies the assumptions of linearity and homoscedasticity, i.e., the error of variance remains constant across fitted values.

Figure 2: Comparison between the Actual Availability Values with Predicted Values.

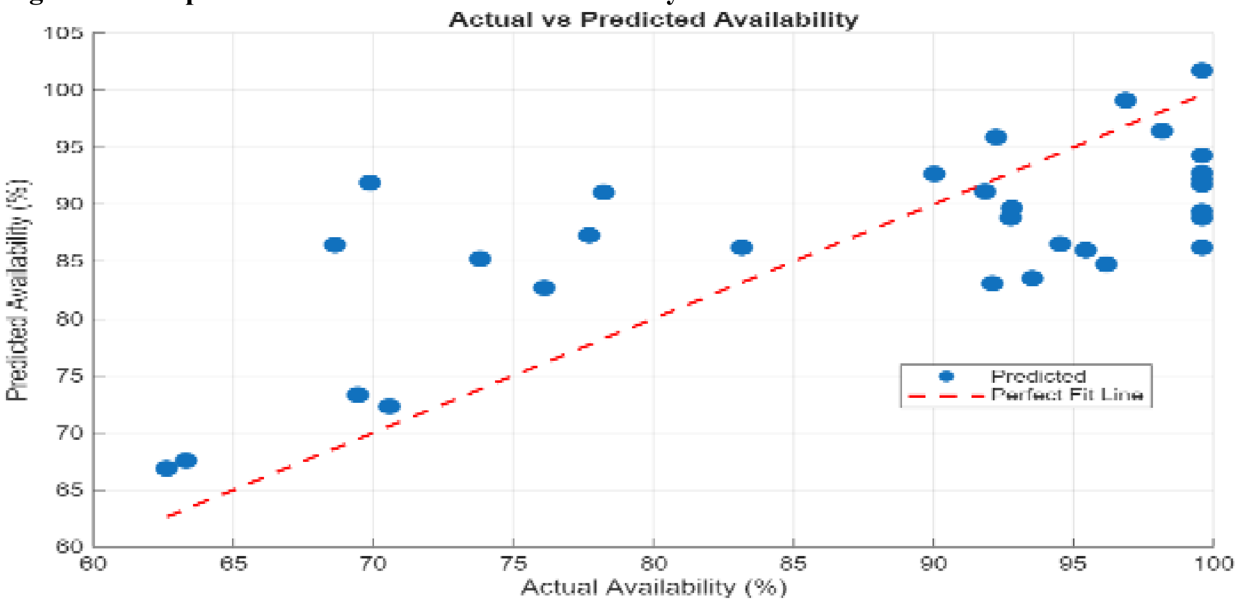

Figure 2 shows that most of the points are aligned closely with the 45° reference line, indicating a good fit. Although some scatter is present as expected in real-world maintenance data, the overall proximity to the reference line confirms that the regression model can reasonably approximate plant availability performance model can reasonably approximate plant availability performance based on the six input factors.

This visual validation aligns with the computed $R^2 = 0.54$, indicating that approximately 54% of the variation in availability is explained by the model. The MAPE = 7.81% further shows a low prediction error, validating the model's usefulness.

Research Gap

The major research gap identified in this section is the lack of a comprehensive and integrated ICT framework for predictive maintenance that is tailored to the specific needs and challenges of thermal power plants in Tanzania. Existing models and studies often focus on specific technologies or industries, limiting their applicability to the unique context of Tanzania. Additionally, the organisational and cultural factors that influence the adoption of ICT for predictive maintenance are not sufficiently addressed. This research fills this gap by developing and validating an ICT integration framework that is specifically designed for thermal power plants in Tanzania, taking into account the unique challenges and opportunities in the region. The framework will be comprehensive, integrating all relevant ICT components, and will be empirically validated in real-world settings to ensure its applicability and scalability.

Several models have been proposed to identify factors influencing the development of ICT integration frameworks for predictive maintenance. A comprehensive framework that integrates various ICT components, including sensors, data analytics, and AI, to enhance predictive maintenance in industrial settings. The model emphasises the importance of real-time data collection and analysis in predicting equipment failures. The work that

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highlights the role of statistical methods and machine learning in fault diagnosis and prognosis provides a robust foundation for developing predictive maintenance systems[7].

METHODOLOGY

The study were conducted at the Ubungo II Gas Plant, one of the thermal power facilities managed by the Tanzania Electric Supply Company (TANESCO), selected as a case study due to its significant contribution to the national grid and frequent maintenance challenges. Data were collected from historical maintenance logs, operational records, Supervisory Control and Data Acquisition (SCADA) systems, and expert input from plant engineers and technicians to capture equipment failure trends and operational parameters such as temperature, pressure, vibration, and fuel consumption. An ICT-based infrastructure was designed to support the predictive maintenance framework, incorporating sensors and IoT devices for real-time monitoring, data management platforms for storage and preprocessing, and analytical tools used were Python libraries (pandas, scikit-learn, TensorFlow), MATLAB, and visualisation dashboards for model development. Data preprocessing involved cleaning, handling missing values, normalisation, and feature engineering to enhance predictive accuracy. The predictive maintenance model was developed through exploratory data analysis, failure mode identification using Failure Mode and Effect Analysis (FMEA), and machine learning techniques, including Random Forest, Support Vector Machines, and Artificial Neural Networks, trained and validated using cross-validation methods. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC metrics [23]. Finally, the validated model was integrated into an ICT platform featuring real-time dashboards, automated alerts, and decision-support modules for maintenance scheduling and resource optimisation, with all data handled under TANESCO's ethical and confidentiality guidelines.

CONCLUSION

The findings substantiate the model's effectiveness in availability forecasting, particularly when based on technical factors extracted from the PCS 7 data set and field maintenance records. The application of statistical techniques provided a demanding and systematic framework for quantitative data analysis. Descriptive statistics were used to summarise the dataset, highlighting key patterns and trends. Correlation analysis revealed significant relationships among variables, while regression analysis identified the critical factors influencing the development of an ICT integration model. This quantitative approach ensures that the research findings are grounded in empirical evidence and supported by robust statistical analysis

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