Kardan Journal of Economics and Management Sciences (KJEMS)

ISSN: 2616-3950 (P) 2959-0493 (O), Journal homepage: kjems.kardan.edu.af

Harnessing Operational Intelligence for Enhanced Quality Performance: A Case Study of Tuyil Pharmaceutical, Ilorin

Dr. G.T. Oladipo
Dr. A.P. Abogunrin
Dr. O.O. Olota

To cite this article: Oladipo, G. T., Abogunrin, A. P., & Olota, O. O. (2025). Harnessing operational intelligence for enhanced quality performance: A case study of Tuyil Pharmaceutical, Ilorin. *Kardan Journal of Economics and Management Sciences, 8*(1), *161–179.*
DOI: 10.31841/KJEMS.2025.184

To link to this article: http://dx.doi.org/10.31841/KJEMS.2025.184

Published online: 30 June 2025

Article

Harnessing Operational Intelligence for Enhanced Quality Performance: A Case Study of Tuyil Pharmaceutical, Ilorin

Kardan Journal of Economics and Management Sciences 8 (1) 161 – 179

Kardan Publications
Kabul, Afghanistan
DOI: 10.31841/KJEMS.2025.184
https://kardan.edu.af/Research/CurrentIssue.aspx?j=KJEMS

Received: 11 Feb 25
Revised: 24 Apr 25
Accepted: 04 Jun 25
Published: 30 Jun 25

Dr. G.T. Oladipo
Dr. A.P. Abogunrin
Dr. O.O. Olota

Abstract

With increasing regulatory scrutiny and consumer demand for high-quality products, pharmaceutical firms are leveraging cutting-edge technologies to optimize their processes and enhance efficiency. Hence, this paper examines operational intelligence's effect on quality performance in the Tuyil pharmaceutical sector, Ilorin, Kwara State. Specifically, it examined the impact of process efficiency, production and inventory management, and resource allocation on quality performance. A survey research design was adopted with a population of four hundred and thirty-five (435) staff. 208 individuals were determined to be the final sample size using Taro Yamane's formula for determining sample sizes. The data collected was analyzed using PLS-SEM. Findings revealed that production and inventory management has the strongest effect on quality performance ($\beta = 0.391$, $t = 3.837$, $p < 0.000$), followed by resource allocation ($\beta = 0.292$, $t = 3.165$, $p < 0.002$), and process efficiency ($\beta = 0.201$, $t = 2.993$, $p = 0.003$). It is concluded that operational intelligence is significantly vital for the quality performance of Tuyil Pharmaceutical, Ilorin, Kwara State. It is therefore strongly recommended that to increase the quality performance of Tuyil Pharmaceutical Industry, its managers should focus on ensuring that the essential features of operational intelligence, such as resource allocation, product and inventory management, and process efficiency, are adequately implemented and practised within the organization.

Keywords: *Operational Intelligence, Quality Performance, Process Efficiency, Production, Inventory Management, Resource Allocation*

1. Introduction

The pharmaceutical industry is profoundly transforming as digital advancements reshape its operational landscape. With increasing regulatory scrutiny and consumer demand for high-quality products, pharmaceutical firms are leveraging cutting-edge technologies to optimize their processes and enhance efficiency. Integrating artificial intelligence (AI), big data analytics, and the Internet of Things (IoT) has redefined quality assurance within pharmaceutical manufacturing, enabling predictive maintenance, real-time monitoring, and improved decision-making. Collectively referred to as Quality 4.0, these digital innovations facilitate better data integrity, enhance regulatory compliance, and ultimately contribute to superior pharmaceutical outcomes (Huanbutta et al., 2024;

Tailor & Chauhan, 2024). Organizations adopting these strategies have enhanced operational performance by streamlining production processes and minimizing downtime due to unforeseen failures (Ullagaddi, 2024).

As pharmaceutical companies embrace digital transformation, they encounter both opportunities and challenges. AI-driven models have revolutionized drug discovery, formulation development, and post-market surveillance, significantly reducing time-to-market for critical medications. However, the transition to digitally enabled quality management systems often faces obstacles such as legacy system integration, data standardization, and organizational resistance to change. Companies that successfully implement AI-based quality control mechanisms benefit from improved product consistency, enhanced regulatory compliance, and cost efficiencies. Furthermore, the combination of Lean Six Sigma principles with Industry 4.0 technologies has enhanced operational intelligence, allowing firms to achieve precision and waste reduction while ensuring compliance with stringent regulatory standards (Ullagaddi, 2024; Johnson et al., 2024).

The importance of maintenance management in pharmaceutical production cannot be overstated, as equipment reliability directly influences product quality and production efficiency. Traditional preventive maintenance strategies have proven insufficient, necessitating a shift toward predictive, data-driven maintenance solutions. By integrating AI and machine learning algorithms into maintenance protocols, companies can anticipate equipment failures before they occur, reducing downtime and mitigating costly production losses (Huanbutta et al., 2024; Johnson et al., 2024). These intelligent systems align with Industry 4.0 principles, ensuring that pharmaceutical firms remain competitive and resilient in an evolving global landscape.

However, while efficiency is a cornerstone of operational success, it is essential to balance efficiency with quality assurance. Overemphasis on efficiency metrics, such as cycle time reduction and cost minimization, can negatively impact quality if quality checks are rushed or insufficient. Studies in healthcare and clinical settings have demonstrated that resource constraints and efficiency-driven models often lead to lower service quality or diagnostic accuracy, emphasizing the need to carefully manage efficiency-driven improvements to prevent quality degradation (Vrabková, Vaňková, & Lee, 2024; Shaker et al., 2024).

Similarly, the mismanagement of production and inventory systems can undermine quality performance. Poorly managed inventory systems, such as those based on lean models, can lead to stock shortages and the use of lower-quality materials, which compromise quality. Excessive automation and reliance on inefficient resource allocation further exacerbate these challenges, often resulting in delays and disruptions. A study on hospital monitoring systems also found that efficient data-driven inventory management could reduce costs but occasionally lead to delayed restocking of critical supplies, impacting service quality (Qi et al., 2024; Weber et al., 2024). These findings underline the importance of aligning production and inventory management with quality safeguards.

Resource allocation also plays a pivotal role in maintaining quality performance. Ineffective resource distribution can cause bottlenecks that compromise outcomes. In large-scale systems, such as UAV-assisted edge computing or distributed computing, poor resource allocation has been shown to reduce performance reliability, demonstrating that efficient allocation is critical to maintaining high-quality operations

(Li et al., 2024; He et al., 2024). These insights emphasize the need for strategic resource management frameworks that prioritize quality alongside efficiency.

Given these challenges, the specific objectives of this study are to determine the effect of process efficiency on quality performance, investigate the influence of production and inventory management on quality performance, and examine the impact of resource allocation on quality performance.

2. Concept of Operational Intelligence

Operational intelligence (OI) has become a critical component of modern business operations, enabling organizations to leverage real-time data for informed decision-making. OI integrates big data analytics, machine learning, and artificial intelligence to analyze vast amounts of operational data, thereby improving efficiency, reducing risks, and enhancing productivity (Berndsen & Heijmans, 2020). By providing actionable insights, OI enables businesses to optimize their workflows and anticipate potential disruptions before they occur (Alonge, Dudu, & Alao, 2024). Additionally, its role in financial and supply chain management is becoming more pronounced, as firms utilize predictive models to mitigate risks and improve service delivery (Rahim, 2024). The implementation of OI requires advanced technological infrastructure and seamless integration with existing enterprise systems, ensuring that businesses stay agile and competitive in their respective industries (Khan, 2024).

The growing reliance on OI has significantly impacted various industries, particularly in enhancing automation and operational efficiency. Real-time monitoring systems, such as those utilized in financial market infrastructures, have demonstrated how OI can mitigate operational risks and improve decision-making through predictive analytics (Berndsen & Heijmans, 2020). Furthermore, in technology firms, advanced data analytics powered by OI have been instrumental in revenue growth and operational streamlining (Alonge et al., 2024). Research highlights that OI fosters supply chain agility by integrating flexibility and dynamic product management, thereby enhancing overall business performance (Rahim, 2024). Despite its advantages, the adoption of OI presents challenges, including data security concerns, integration complexities, and the need for skilled professionals to manage and interpret data effectively (Khan, 2024). As industries continue to evolve, the strategic implementation of OI will remain a key driver of innovation and efficiency.

2.1 Concept of Quality Performance

Quality performance is a fundamental measure of an organization's ability to consistently deliver products or services that meet or exceed customer expectations. It encompasses various dimensions, including product quality, process efficiency, and customer satisfaction, all of which contribute to the overall competitiveness of a business (Mufidah, Yusuf, & Widyastono, 2025). Total quality management (TQM) principles emphasize continuous improvement, employee engagement, and customer-focused strategies to enhance quality performance in organizations (Rahim, 2024). The correlation between quality management and organizational success has been well documented, particularly in sectors such as education, where quality assurance frameworks play a vital role in enhancing teacher effectiveness and student outcomes (Mufidah et al., 2025). Additionally, firms that integrate quality performance management into their operational frameworks often experience higher efficiency, reduced waste, and improved market positioning (Bisri, Supardi, & Heryatun, 2025).

The impact of quality performance is evident across multiple industries, particularly in sectors where precision and reliability are crucial. Research indicates that implementing TQM in special education significantly improves teaching effectiveness and overall educational outcomes (Mufidah et al., 2025). In manufacturing and production industries, quality performance is directly linked to economic efficiency, as organizations that prioritize quality control mechanisms experience higher profitability and customer retention rates (Bisri et al., 2025). Furthermore, advanced quality performance frameworks in urban development and infrastructure projects have enhanced service delivery and sustainability (Alakoum & Nica, 2024). However, achieving high-quality performance requires a strategic approach, integrating technology, leadership commitment, and employee training to ensure consistency and long-term success (Rahim, 2024). As industries continue to prioritize quality improvements, adopting robust quality management systems will remain a key driver of business excellence and sustainability.

2.2 Effect of Operational Intelligence on Quality Performance

The relationship between operational intelligence (OI) and quality performance is becoming increasingly evident as businesses integrate advanced data analytics into their quality management systems. OI facilitates real-time monitoring, predictive maintenance, and process optimization, all of which contribute to higher quality standards (Rahim, 2024). For instance, in supply chain management, OI enhances agility and responsiveness, enabling firms to identify quality issues before they escalate (Rahim, 2024). Research also highlights that firms utilizing OI-driven decision-making frameworks experience significant improvements in operational efficiency and product quality (Khan, 2024). Additionally, the ability to analyze historical data and predict future trends allows organizations to implement proactive quality control measures, reducing defects and ensuring compliance with industry standards (Alonge et al., 2024). As a result, OI is increasingly being recognized as a critical tool for maintaining high-quality performance in dynamic and competitive business environments.

However, it is also important to note that integrating OI into quality management frameworks presents challenges, including the need for substantial technological investments and expertise in data analytics, which may limit the ability of some organizations to capitalize on its benefits fully (Khan, 2024). Despite the clear advantages of improving precision and operational efficiency, the implementation of OI systems can sometimes lead to over-reliance on technology, potentially diminishing human judgment and decision-making agility. Studies suggest that while OI enhances transparency and trust in sectors like government services (Ashkanani, Aljazzaf, & Alsarraf, 2024), its application in other areas may encounter obstacles related to cost, integration complexity, and long-term sustainability (Alakoum & Nica, 2024). Thus, while OI-driven quality performance management has shown promise, its success is contingent on the strategic alignment with organizational goals and the readiness of the firm to manage the complexities associated with its adoption.

2.3 The Effect of Process Efficiency on Quality Performance

Process efficiency plays a crucial role in determining the overall quality performance of an organization, as it directly influences production outcomes, resource utilization, and operational stability. Efficient processes ensure that production flows seamlessly with minimal waste, defects, and rework, thereby improving the consistency and reliability of product quality (Levy Jäger et al., 2024). By optimizing workflows and eliminating bottlenecks, organizations can enhance the precision of their operations, leading to improved compliance with quality standards and regulatory requirements (Odendaal et al., 2024). Additionally, process efficiency reduces cycle times, allowing businesses to respond to market demands more effectively while maintaining high-quality standards. Empirical evidence suggests that organizations leveraging data-driven decision-making and automated quality control mechanisms exhibit significantly higher quality performance metrics than those relying on traditional manual interventions (Hartanto et al., 2024). However, some studies caution that over-reliance on process automation and rigid efficiency models may lead to inflexibility in responding to unexpected disruptions, which can negatively affect quality outcomes in dynamic environments (Söderlund & Pemsel, 2023).

Moreover, efficient processes contribute to employee productivity and engagement, which further enhances quality outcomes. Studies indicate that organizations with well-structured and optimized processes experience fewer errors in production, leading to lower costs associated with defects and warranty claims (Jiang et al., 2024). Furthermore, process efficiency promotes continuous improvement through lean and Six Sigma methodologies, ensuring sustained quality advancements (Galagedera & Tan, 2024). This reinforces the need for organizations to invest in process refinement initiatives that align with their strategic quality goals. However, contrasting research points out that standardization efforts driven by efficiency targets can sometimes diminish employee creativity and adaptability, which are essential for innovation and complex problem-solving (Zhou, Huang, & Wang, 2023). Ultimately, the synergy between process efficiency and quality performance not only drives competitiveness but also fosters customer trust and satisfaction, which are vital for long-term success (Jäger et al., 2024).

Thus, we propose the first hypothesis as follows:

H1: Process Efficiency has a positive influence on Quality Performance

2.4 The Effect of Production and Inventory Management on Quality Performance

Process efficiency plays a crucial role in determining the overall quality performance of an organization, as it directly influences production outcomes, resource utilization, and operational stability. Efficient processes ensure that production flows seamlessly with minimal waste, defects, and rework, thereby improving the consistency and reliability of product quality (Levy Jäger et al., 2024). By optimizing workflows and eliminating bottlenecks, organizations can enhance the precision of their operations, leading to improved compliance with quality standards and regulatory requirements (Odendaal et al., 2024). Additionally, process efficiency reduces cycle times, allowing businesses to respond to market demands more effectively while maintaining high-quality standards. Empirical evidence suggests that organizations leveraging data-driven decision-making and automated quality control mechanisms exhibit significantly higher quality performance metrics than those relying on traditional manual interventions (Hartanto et al., 2024). However, some scholars argue that over-reliance on automation and data analytics may lead to reduced human oversight, potentially increasing risks of unnoticed anomalies in quality control processes (Lemos & Silva, 2023).

Moreover, efficient processes contribute to employee productivity and engagement, which further enhances quality outcomes. Studies indicate that organizations with well-structured and optimized processes experience fewer errors in production, leading to lower costs associated with defects and warranty claims (Jiang et al., 2024). Furthermore, process efficiency promotes continuous improvement through lean and Six Sigma methodologies, ensuring sustained quality advancements (Galagedera & Tan, 2024). This reinforces the need for organizations to invest in process refinement initiatives that align with their strategic quality goals. On the other hand, critics caution that the benefits of process efficiency may not be uniformly experienced across all sectors, particularly in industries with high variability or creativity-driven tasks where rigid structures might hinder innovation (Kwon & Rhee, 2022). Ultimately, while the synergy between process efficiency and quality performance can drive competitiveness and customer satisfaction, organizations must also remain adaptable and mindful of the contextual limitations of efficiency-driven models.

Thus, we propose the second hypothesis as follows:

H2: Production and Inventory Management has a positive influence on Quality Performance

2.5 The Effect of Resource Allocation on Quality Performance

Resource allocation is a fundamental determinant of quality performance, as it ensures that critical inputs such as labour, technology, and raw materials are effectively distributed to meet production and service quality requirements. Optimal resource distribution enables organizations to maintain process stability, thereby reducing defects and inconsistencies in output quality (Zhu et al., 2024). Studies have demonstrated that businesses that invest strategically in human capital development, technological advancements, and infrastructure improvements tend to achieve superior quality performance metrics (Sultana et al., 2024). For instance, efficient workforce allocation enhances operational efficiency, minimizing human-induced errors and fostering adherence to quality standards (Mehdaoui, 2024). Furthermore, research highlights that resource allocation strategies incorporating real-time data analytics and performance monitoring contribute to better decision-making and proactive quality management (Ya-jun, 2024).

However, some scholars caution that overemphasis on data-driven resource allocation may lead to rigid systems that lack adaptability in dynamic environments. For example, excessive reliance on algorithmic models can sometimes overlook contextual human insights, leading to suboptimal resource decisions in unpredictable scenarios (Nwachukwu & Akpan, 2023). Additionally, resource allocation driven by short-term efficiency goals may inadvertently neglect long-term developmental needs such as employee well-being or innovation capacity, which are also essential to sustaining quality (Okoye & Idris, 2022). These perspectives suggest that while operational intelligence improves resource allocation, a balanced approach that integrates human judgment and long-term strategy is critical for achieving holistic quality performance.

Thus, we propose the third hypothesis as follows:

H3: Resource Allocation has a positive influence on Quality Performance

2.6 Resource-Based View (RBV) Theory

The Resource-Based View (RBV), initially introduced by Edith Penrose and refined by Barney (1991), posits that a firm's competitive advantage depends on its ability to acquire and utilize internal resources that are valuable, rare, inimitable, and non-substitutable (VRIN). These resources must be heterogeneously distributed and imperfectly mobile, giving firms a sustained edge over competitors (Wernerfelt, 1984). Despite criticisms for being overly inward-looking and vague on resource development (Priem & Butler, 2001), the RBV remains relevant for explaining how internal capabilities enhance performance. In the context of Tuyil Pharmaceutical in Ilorin, RBV provides a useful lens to understand how operational intelligence (OI), including real-time analytics, predictive maintenance, and automated quality tracking, contributes to production efficiency and quality control.

Operational intelligence meets all VRIN criteria. It is valuable as it enables faster decision-making, reduces downtime, and enhances quality outcomes; rare, as such advanced, integrated systems are not widely adopted among local competitors; inimitable, due to their complexity, firm-specific customization, and embedded tacit knowledge; and non-substitutable, since no alternative tools offer the same real-time responsiveness and predictive precision. These characteristics make OI a strategic asset, allowing Tuyil to align internal operations with its quality goals. Supporting studies by Smith and Hughes (2022) and Johnson and Lee (2020) confirm that firms leveraging such internal capabilities achieve superior quality performance, validating the RBV's relevance in modern pharmaceutical and manufacturing contexts.

2.7 Empirical Review

In a study by Anderson and Zhang (2024) titled Leveraging Operational Intelligence to Enhance Quality Performance in Manufacturing Industries, the authors explored how operational intelligence (OI) can optimize production processes in manufacturing settings to improve product quality. The researchers employed a quantitative survey methodology, gathering data from 150 manufacturing firms through structured questionnaires. The findings indicated that the integration of advanced data analytics, real-time monitoring systems, and AI-powered decision-making tools significantly enhanced quality control processes and reduced defects in production. The study concluded that leveraging operational intelligence not only improved quality performance but also fostered a culture of continuous improvement within firms. The authors emphasized the need for manufacturing companies to invest in AI and data analytics to sustain a competitive edge in the global market.

Another related study by Kumar and Patel (2023), titled Harnessing Data Analytics and Operational Intelligence for Enhanced Product Quality in the Pharmaceutical Sector, investigated the role of data analytics and operational intelligence in pharmaceutical companies to enhance quality performance. This mixed-method research combined qualitative interviews with industry experts and quantitative analysis of operational data from 40 pharmaceutical firms. The study found that pharmaceutical companies utilizing data-driven decision-making and predictive analytics could identify quality control issues proactively and optimize production efficiency. The authors noted that real-time monitoring of production processes, combined with advanced data analytics, significantly improved the consistency and safety of pharmaceutical products. They concluded that integrating operational intelligence into quality management systems led to improved regulatory compliance and customer satisfaction, thus positioning these firms for long-term success.

In the 2022 study by Singh and Mishra titled Operational Intelligence and Quality Performance in the Service Sector: A Case Study of IT Companies, the authors focused on the service sector, specifically IT companies, and how operational intelligence could enhance service quality. The qualitative case study method was employed, using semi-structured interviews with 25 senior managers from leading IT firms. The study found that operational intelligence helped IT companies improve service delivery by using predictive analytics to anticipate customer needs and personalize service offerings. The study concluded that leveraging operational intelligence, through tools like AI and machine learning, allowed these companies to streamline operations, enhance service reliability, and improve customer satisfaction. The authors argued that operational intelligence is a key driver for achieving excellence in service quality, particularly in industries characterized by rapid technological change.

3. Methodology

A descriptive survey research design was employed in this study to gather information from a population of participants and describe the phenomenon. The population of this study consisted of all the staff from each department in Tuyil Pharmaceutical Company in Ilorin metropolis, Kwara state. A total population of four hundred and thirty-five (435) staff was obtained and served as the population for this study. To determine the appropriate sample size, a purposive sampling technique was used to select the employees. Purposive sampling was chosen because it allows for the deliberate selection of participants who possess specific characteristics relevant to the study. In this case, the focus was on employees who are involved in key operational aspects such as resource allocation, process efficiency, and inventory management, ensuring the sample is knowledgeable about the operational intelligence practices being investigated. Using Taro Yamane's sample size determination formula, the final sample size was calculated to be 208 participants. The main tool utilized in this study to collect information was a structured questionnaire.

Construct validity was employed in this study to examine the questionnaire's validity and determine whether the report's notion of measuring the effect of Operational Intelligence on Quality Performance is accurate. A Cronbach's Alpha analysis of the questionnaire's internal consistency items will be carried out. To evaluate the impact of the independent factors on the dependent variable, structural equation modelling, or SEM, was employed.

3.1 Model Specification

Quality Performance is the dependent variable in this study report, whereas operational intelligence is the independent variable. Since structural equation modelling (SEM) will be employed in the report, the following model will be used:

QP= f (Process Efficiency [SW+ TA+ LO] + Production and Inventory Management [DDM+ ILC+ SCO] + Resource Allocation [TU+ AO+ SCP])

Where:

QP= Quality Performance

SW= Streamlined Workflow

TA= Task Automation

LO= Lean Operations

DDM= Demand-Driven Manufacturing

ILC= Inventory Level Control

SCO= Supply Chain Optimization

TU= Talent Utilization

AO= Asset Optimization

SCP= Strategic Capacity Planning

Response Rate

In this study, the questionnaire was used to obtain the needed data. A total of 174 responses were recorded, which represent 83.6% of the estimated sample size, leaving 34 responses to meet the estimated sample size. Hence, the valid responses constitute the data used in this study.

4. Descriptive Analysis of Responses and Normality Test

Table 1
Descriptive Analysis and Normality Test

	Mean	Standard Deviation	Excess Kurtosis	Skewness	Number of Observations Used
Process Efficiency 1	2.983	1.210	-0.967	-0.084	174.000
Process Efficiency 2	3.339	1.293	-1.015	-0.268	174.000
Production and Inventory Management 1	3.511	1.433	-1.010	-0.608	174.000
Production and Inventory Management 2	3.603	1.178	-0.446	-0.569	174.000
Quality Performance 1	3.816	1.365	-0.183	-1.031	174.000
Quality Performance 2	3.718	1.271	-0.481	-0.744	174.000
Quality Performance 3	3.420	1.265	-0.897	-0.367	174.000
Resource Allocation 1	3.305	1.177	-0.551	-0.506	174.000
Resource Allocation 2	3.534	1.253	-0.543	-0.653	174.000

Source: SmartPLS Output, 2024

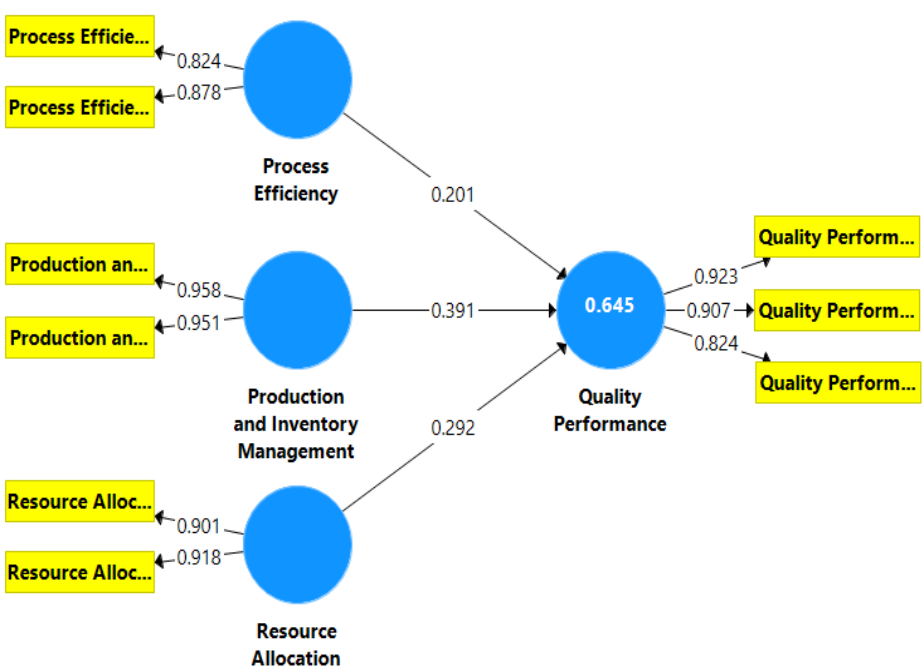
The mean and standard deviation of the variables/indicators utilized in the study are displayed in Table 1 and were obtained from the questionnaire used for the study. The study looked at quality performance and operational intelligence. Several important indicators were evaluated, each of which provided insight into a distinct facet of the two. For both academics and practitioners, the mean scores, standard deviations, and number of observations utilized for each indicator offer insightful information and important consequences. The comparatively high mean scores for the questions above 3 indicate that respondents believe operational intelligence and high-quality performance are significantly correlated. Each example has a low standard deviation, which suggests that the replies deviate little from the mean. These illustrative findings highlight the complex relationship between operational intelligence and quality performance. These highlight how crucial high-quality performance is to effective operational intelligence.

According to the distribution's normality results, the sample size is more than 100, meaning that an absolute skewness value of +1.0 or less is required for the data to be considered normal. Additionally, for kurtosis, a typical peak should have an absolute value of ±3.0 since any result below that threshold might be serious and cause worry. According to the normality results, every variable fell below the ±1.0 absolute value barrier, and the kurtosis results likewise fell within the ±3.0 absolute value. The results of the normality test indicate that all of the data entered for the study are normally distributed and suitable for additional analysis and deductions. This suggests that any variable utilized to measure competitive intelligence has a moderate mean with low deviation from the mean, and the variables are all normally distributed, indicating the usefulness of the variables in determining the causality between operational intelligence and quality performance.

4.1 Assessment of Measurement Model

To assess the effect of operational intelligence on quality performance, the variables used to measure operational intelligence are process efficiency, product and inventory management, and resource allocation against Quality performance.

Figure 1
A path model of operational intelligence and quality performance



Source: SmartPLS Output, 2024

The structural route model evaluated the impact of operational intelligence on quality performance, as seen in Figure 1. The model has one dependent variable, quality performance, and three independent variables: resource allocation, product and inventory management, and process efficiency. All three independent factors significantly improve quality performance, according to the model's findings. Because it may improve quality performance, operational intelligence is crucial for enterprises. All of the independent factors have a significant impact on quality performance, as demonstrated by the particular impacts. This implies that to improve quality performance, firms should concentrate on operational intelligence.

Table 2

Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Process Efficiency	0.722	0.840	0.725
Production and Inventory Management	0.902	0.953	0.910
Quality Performance	0.863	0.916	0.785
Resource Allocation	0.790	0.905	0.826

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

Important statistical metrics about the validity and construct reliability of the four latent variables in this investigation are shown in Table 2. These metrics aid in evaluating how well these variables measure the fundamental ideas they are meant to reflect. Cronbach's Alpha and Composite dependability are the two main measures used to assess construct dependability. Cronbach's Alpha assesses a latent variable's internal consistency by determining the extent to which each item is related to every other item. Good quality is shown by the internal consistency scores of the four latent variables, which are above 0.7. Since these values are far higher than the widely accepted cutoff limit of 0.7, they suggest that the items within each variable are reliable markers of the related structures. Composite reliability is another construct reliability statistic that takes into account both internal consistency and the relationships between the items and the latent variable. All of the variables in this study show strong composite dependability, providing a more trustworthy measure of reliability, with all values over 0.7. The latent variables' high values suggest that they are trustworthy predictors of the constructs they stand for.

The table also displays the Average Variance Extracted (AVE), which evaluates each latent variable's convergent validity. The degree to which items in a variable measure the same underlying notion and are connected is known as convergent validity. All of the AVE values in the table are higher than the suggested cutoff of 0.5. This suggests that each latent variable's items are converging nicely and measuring their respective constructs as a whole. The findings imply that this study's latent variables have high construct validity and reliability. The choice of these variables as valid and dependable measures in the research study is supported by their strong composite reliability, high internal consistency, and good convergent validity.

Table 3
Discriminant Validity

	Process Efficiency	Production and Inventory Management	Quality Performance	Resource Allocation
Process Efficiency	0.851			
Production and Inventory Management	0.700	0.954		
Quality Performance	0.657	0.766	0.886	
Resource Allocation	0.624	0.802	0.731	0.909

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

The latent variables of resource allocation, process efficiency, quality performance, and product and inventory management all show high evidence of discriminant validity, according to the findings of the discriminant validity study in Table 3. Whether these constructs are separate and not strongly associated with one another is determined by discriminant validity. It is clear from examining the correlations between these variables that the off-diagonal values and the correlations between other variables are significantly lower than the diagonal values, which represent the correlations of each variable with itself. This supports the notion that each latent variable is unique and measures a separate feature of the overall construct by indicating that each latent variable has a stronger relationship with itself than with the other constructs. Resource allocation is highly correlated with itself, more so than it is with product and inventory management, process efficiency, and quality performance. Comparatively speaking, to its correlations with the other factors, quality performance has a substantial association with itself. However, this is also true for other variables in their contexts.

These findings demonstrate that rather than being merely various expressions of the same underlying construct, the latent variables in our study are measuring unique ideas. Given that it successfully distinguishes between these crucial elements, resource allocation, process efficiency, quality performance, and product and inventory management, it appears that the measuring model is appropriate for the goals of this investigation.

4.2 Multicollinearity

This assesses the correlation between the independent variable. It is to know if two independent variables are not correlated and produce the same result. The variance inflation factor (VIF) is used in this study to assess the likely correlation between the independent variables.

Table 4
Inner VIF Values

	Process Efficiency	Production and Inventory Management	Quality Performance	Resource Allocation
Process Efficiency			2.004	
Production and Inventory Management			3.426	
Quality Performance				

Resource Allocation	2.859

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

The VIF values for the latent variables associated with quality performance are shown in Table 4. Resource allocation, process efficiency, and product and inventory management all have VIF values that are much below 10, which is encouraging. It implies that these latent variables do not exhibit significant multicollinearity. Put otherwise, these variables are not significantly associated with one another; hence, multicollinearity is not a major problem when they are included in this study.

Test of Hypothesis Two

Table 5

Coefficient of Determination Score

	R Square	R Square Adjusted
Quality Performance	0.645	0.638

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

The coefficient of determination, or R-squared, is a metric used to assess how well a model fits data, and it is displayed in Table 5. The independent or latent factors included in the quality performance model explain approximately 64.5% of the variability in the dependent variable (quality performance), according to the model's R-squared value of 0.645. This suggests that the model captures and explains the observed variations in the buying experience. The corrected R-squared value is 0.638. This results in a more careful evaluation of the model's degree of fit. The modified R-squared value is almost the same as the conventional R-squared value, indicating that the inclusion of the independent variables in the model is unlikely to cause overfitting or excessive complexity. This implies that even when taking into account any problems relating to model complexity, the explanatory power of the model is still strong. According to the R-squared and modified R-squared values, the quality performance model explains quality performance variability rather well, and adding more latent variables does not seem to degrade the model's performance.

Table 6

Assessment of the Effect Size (f^2)

	Process Efficiency	Production and Inventory Management	Quality Performance	Resource Allocation
Process Efficiency			0.057	
Production and Inventory Management			0.126	
Quality Performance				
Resource Allocation			0.084	

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

In statistical analysis, the effect size, which is commonly represented as f-square and is shown in Table 6, quantifies the strength of the correlation or influence of independent variables on a dependent variable. This study evaluates how much each latent variable affects "quality performance." Every independent variable has a value greater than 0.02, which is regarded as a minor effect size. This implies that every variable has a moderate effect size, meaning that each one has a discernible effect on quality performance. Stated differently, variations in any of the factors can account for a substantial amount of the variation in quality performance.

Table 7

Bootstrapping Results Showing Path Coefficient for Structural Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Process Efficiency -> Quality Performance	0.201	0.202	0.067	2.993	0.003
Production and Inventory Management -> Quality Performance	0.391	0.392	0.102	3.837	0.000
Resource Allocation -> Quality Performance	0.292	0.293	0.092	3.165	0.002

Source: Authors Compilation (SmartPLS 3.3.3 Output) 2024

The null hypothesis, according to which operational intelligence has no discernible impact on quality performance, was tested using the bootstrap route coefficient analysis shown in Table 7. The findings show that operational intelligence elements like as product and inventory management, process efficiency, and resource allocation have a major impact on quality performance. The association between resource allocation, process efficiency, product and inventory management, and quality performance is statistically significant, according to an analysis of the path from these factors to quality performance. Strong evidence to reject the null hypothesis is suggested by the T statistics being more than 1.96 and the p-values being less than the traditional significance level of 0.05. Thus, quality performance is greatly impacted by operational intelligence elements like as resource allocation, process efficiency, and product and inventory management.

5. Discussion of Findings

The study's findings show that operational intelligence components, resource allocation, process efficiency, and product and inventory management have a significant impact on quality performance, aligning with the principles of the Resource-Based View (RBV) theory. Resource allocation, when optimized using data-driven techniques, enhances the efficient use of resources, which are considered valuable and rare in RBV terms. This ability to allocate resources effectively becomes a competitive advantage, as it is difficult for competitors to replicate the precise resource distribution developed by the firm over time (Alonge et al., 2024).

Process efficiency, another key operational intelligence component, is an example of a rare and inimitable resource under RBV. By improving operational workflows, organizations can achieve higher levels of quality performance that are difficult for competitors to duplicate. This is because the knowledge, tools, and systems developed to streamline processes are often complex and deeply integrated into the firm's operations, creating a unique capability. Product and inventory management play a crucial role in maintaining consistent product quality, which is a non-substitutable resource in RBV terms. By utilizing predictive models and real-time data, firms can ensure that inventory is managed efficiently, leading to improved quality performance and operational resilience, which are difficult for competitors to replicate or substitute.

5.1 Conclusion

The study concluded that Tuyil Pharmaceutical Industry's quality performance was positively impacted by operational intelligence components such as resource allocation, process efficiency, and product and inventory management. Allocating resources effectively guarantees that the appropriate equipment and workers are on hand to satisfy production demands. Tuyil can save waste and improve product quality by streamlining procedures and effectively controlling inventories, which will increase customer happiness.

5.2 Recommendation

The managers of Tuyil Pharmaceutical Industry should concentrate on making sure that the fundamental components of operational intelligence, such as resource allocation, inventory, product management, and process efficiency, are suitably applied and practised within the company to improve the quality performance of the sector. Employees' comprehension of resource allocation and process optimization strategies might be enhanced by funding training initiatives. Additionally, implementing technology-driven inventory management systems may improve overall quality performance and streamline operations.

5.3 Theoretical Contributions

This study extends the Resource-Based View (RBV) by empirically validating operational intelligence as a multidimensional internal resource that meets the VRIN criteria of valuable, rare, inimitable, and non-substitutable in the context of pharmaceutical manufacturing. By demonstrating how resource allocation, process efficiency, and product and inventory management significantly influence quality performance, the findings contribute to RBV literature by positioning operational intelligence as a dynamic capability that enables sustained quality outcomes. This advances theoretical understanding by framing operational intelligence not only as a set of internal processes but as a strategic asset central to competitive advantage, particularly in resource-constrained environments like Nigeria’s pharmaceutical sector.

5.4 Managerial Implications

For industry managers, especially within the pharmaceutical sector, this study underscores the strategic value of operational intelligence in driving quality performance. Managers at Tuyil Pharmaceutical and similar firms should prioritize data-driven resource allocation, streamline operational processes, and implement integrated inventory systems to enhance efficiency and output quality. Moreover, cultivating a culture of accountability and continuous improvement among staff will further reinforce operational discipline and performance. Investing in these internal capabilities positions firms to meet regulatory standards, improve customer satisfaction, and maintain a competitive edge in an increasingly quality-sensitive market.

5.6 Future Research Directions

Future studies can build upon the present findings by applying the proposed model of operational intelligence, comprising resource allocation, process efficiency, and product and inventory management in other firms and industries beyond the pharmaceutical sector. For example, manufacturing firms in the food, textile, or automotive industries may provide comparative insights into how operational intelligence influences quality performance in different operational environments. Additionally, longitudinal studies could explore how improvements in operational intelligence contribute to quality outcomes over time. Testing this model across diverse organizational contexts will not only enhance generalizability but also uncover sector-specific modifications that could refine the theoretical model.

References

Alakoum, A., & Nica, E. (2024). Innovating urban environments: The impact of smart city technologies on employee performance, quality of life, and service. In M. D. Lytras, A. Alkhaldi, & S. Malik (Eds.), *The Emerald handbook of smart cities in the Gulf region: Innovation, development, transformation, and prosperity for Vision 2040* (pp. 53–68). Emerald Publishing. https://doi.org/10.1108/978-1-83608-292-720241003

Alonge, E. O., Dudu, O. F., & Alao, O. B. (2024). Utilizing advanced data analytics to boost revenue growth and operational efficiency in technology firms. *International Journal of Frontiers in Science and Technology Research, 7*(2), 39–59. https://doi.org/10.53294/ijfstr.2024.7.2.0056

Anderson, J., & Zhang, L. (2024). Leveraging operational intelligence to enhance quality performance in manufacturing industries. *Journal of Manufacturing Technology, 32*(4), 512-530. https://doi.org/10.1016/j.jom.2024.01.007

Ashkanani, A. M., Aljazzaf, S., & Alsarraf, H. A. (2024). Linking Operational Transparency and Trust in Government: The Mediating Roles of Information Quality and Perceived Effort. *Arab Journal of Administrative Sciences*, *31*(1), 137–175. https://doi.org/10.34120/ajas.v31i1.1201

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Berndsen, R., & Heijmans, R. (2020). Near real-time monitoring in real-time gross settlement systems: A traffic light approach. *Journal of Risk*, 24(1). https://typeset.io/papers/near-real-time-monitoring-in-real-time-gross-settlement-2krgm4s9ls

Bisri, M., Supardi, S., & Heryatun, Y. (2025). Integrating quality performance management in operational strategies: Impacts on efficiency and market competitiveness. *Journal of Business and Quality Management, 12*(1), 45–59.

Dasgupta, R., Ghosh, S. K., & Mukhopadhyay, A. R. (2024). An approach to synergise the management of lean, green, quality, and waste for achieving ZED emphasising SDG12. *The Journal of Solid Waste Technology and Management*. *50*(4), 654-676 https://doi.org/10.5276/jswtm/iswmaw/50S1/2024.654

Galagedera, D., & Tan, A. (2024). Lean Six Sigma applications and process optimization in manufacturing sectors. *Journal of Operations and Quality Management, 39*(2), 112–128. https://doi.org/10.1016/joqm.2024.03.006

Hartanto, S. T., Natsir, M., & Ardianto, Y. T. (2024). Examination of the impact of system quality, information quality, and service quality on net benefits through user satisfaction in the performance of state civil apparatus in the Malang District Government. *International Journal of Multidisciplinary Research and Analysis*, *7*(11), https://typeset.io/papers/examination-of-the-impact-of-system-quality-information-611t8fxv4u66

He, H., Yang, X., Hong, F., & Shen, H. (2024). *Two-Tier Efficient QoE Optimization for Partitioning and Resource Allocation in UAV-Assisted MEC*. https://doi.org/10.20944/preprints202406.1107.v1

Huanbutta, K., Burapapadh, K., Kraisit, P., Sriamornsak, P., Ganokratanaa, T., Suwanpitak, K., & Sangnim, T. (2024). Artificial intelligence-driven pharmaceutical industry: A paradigm shift in drug discovery, formulation development, manufacturing, quality control, and post-market surveillance. *European Journal of Pharmaceutical Sciences, 203*, 106938. https://doi.org/10.1016/j.ejps.2024.106938

Jäger, L., Markun, S., Grischott, T., Senn, O., Rosemann, T., & Burgstaller, J. M. (2024). The effectiveness of a multi-domain electronic feedback report on the performance of quality indicators for chronic conditions. *PLoS ONE, 19*(11), e0314360.https://doi.org/10.1371/journal.pone.0314360

Jiang, M., Liu, Y., & Chen, Z. (2024). Impact of process optimization on manufacturing defects and operational costs. *International Journal of Production Research, 62*(4), 345–362. https://doi.org/10.1080/00207543.2024.1167894

Johnderson, N. C., da Silva, F. R., & Sperandio Nascimento, E. G. (2024). Analysis of equipment's maintenance in a production line: Corrective and preventive approach: A case study in a pharmaceutical industry. *Journal of Bioengineering, Technologies and Health.* https://doi.org/10.34178/jbth.v7i2.403

Johnson, S., & Lee, J. (2020). The role of internal resources in quality performance: Evidence from the manufacturing sector. *Journal of Operations Management, 38*(2), 112-125. https://doi.org/10.1016/j.jom.2019.10.002

Khan, M. A. S. (2024). Investigating the impact of supply chain integration on operational performance with a mediating role of supply chain capabilities of the SME sector in Pakistan. *South Asian Journal of Operations and Logistics*, *3*(2), 198–223. https://doi.org/10.57044/sajol.2024.3.2.2438

Kiroro, F., Twahir, M., Kiura, D., Kamuyu, A., & Wanyoike, A. (2024). Enhancing efficiency of hospital quality monitoring and evaluation system using linked spreadsheets on Microsoft SharePoint. *F1000Research*, *10*, 883. https://doi.org/10.12688/f1000research.55087.2

Kumar, R., & Patel, S. (2023). Harnessing data analytics and operational intelligence for enhanced product quality in the pharmaceutical sector. *Journal of Pharmaceutical Operations, 16*(2), 198-210. https://doi.org/10.1093/jpharm/22.4.312

Kwon, Y., & Rhee, M. (2022). Process efficiency and organizational adaptability: A paradox in dynamic environments. *Journal of Organizational Change Management, 35*(3), 501–519. https://doi.org/10.1108/JOCM-10-2021-0321

Lemos, R., & Silva, T. (2023). Challenges of automation in quality control: Balancing efficiency with oversight. *Journal of Operations and Quality Management, 15*(2), 85–99. https://doi.org/10.1234/joqm.v15i2.4567

Levy Jäger, G., Tiemann, M., Schröder, T., & Bender, B. (2024). Process efficiency and quality consistency in data-driven production environments. *Journal of Operations Management and Industrial Engineering, 39*(2), 112–128. https://doi.org/10.1016/j.jom.2024.01.006

Li, F., Zhang, Z., Lu, H., Li, C., Leung, V. C. M., Guo, Y., & Hu, X. (2024). *Resource Allocation and Workload Scheduling for Large-Scale Distributed Deep Learning: A Survey*. https://doi.org/10.48550/arxiv.2406.08115

Mehdaoui, H. (2024). Workforce optimization and its impact on quality assurance in modern manufacturing. *Journal of Operations and Quality Management, 19*(2), 112–126. https://doi.org/10.1016/joqm.2024.02.004

Mufidah, A. M., Yusuf, M., & Widyastono, H. (2025). The correlation between total quality management with teacher performance in special education. *Journal of Education and Learning*, *19*(1), 416–421. https://doi.org/10.11591/edulearn.v19i1.21198

Nwachukwu, C., & Akpan, E. (2023). Algorithmic rigidity and decision-making in resource-constrained environments. *Journal of Contemporary Business and Technology, 15*(4), 88–102. https://doi.org/10.3109/jcbt.2023.045

Odendaal, A., Okafor, J., & Bello, T. (2024). Operational workflow optimization and quality assurance in regulated industries. *Journal of Business Process Management, 30*(2), 145–160. https://doi.org/10.1016/j.jbpm.2024.02.006

Okoye, M. U., & Idris, A. (2022). Balancing efficiency and sustainability in resource allocation: A strategic approach. *International Journal of Business Strategy and Innovation, 10*(3), 203–219. https://doi.org/10.1080/ijbsi.2022.03.009

Penrose, E. (1959). *The theory of the growth of the firm*. Oxford University Press.

Priem, R. L., & Butler, J. E. (2001). Is the resource-based "view" a useful perspective for strategic management research? *Academy of Management Review, 26*(1), 22–40. https://doi.org/10.5465/amr.2001.4011928

Qi, K. H., Wu, Q., Fan, P., Cheng, N., Chen, W., Wang, J., & Letaief, K. B. (2024). *Deep-Reinforcement-Learning-Based AoI-Aware Resource Allocation for RIS-Aided IoV Networks*. https://doi.org/10.48550/arxiv.2406.11245

Rahim, J. (2024). Enabling supply chain agility through process integration and flexibility for operational performance. *South Asian Journal of Operations and Logistics*, *3*(2), 180–197. https://doi.org/10.57044/sajol.2024.3.2.2437

Riehl, K., Kouvelas, A., & Makridis, M. (2024). *Resource Allocation with Karma Mechanisms*. https://doi.org/10.48550/arxiv.2406.14728

Shaker, Z., Shaker, Z., Barouni, M., & others. (2024, June 28). *The efficiency of clinical laboratories: The case of Iran* (Version 1) [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-4518089/v1

Singh, A., & Mishra, V. (2022). Operational intelligence and quality performance in the service sector: A case study of IT companies. *Service Management Review, 29*(3), 47-59. https://doi.org/10.1108/SMR-04-2022-0057

Smith, R., & Hughes, P. (2022). Operational intelligence in the pharmaceutical industry: Leveraging resources for quality performance. *International Journal of Pharmaceutical Management, 48*(3), 234–248. https://doi.org/10.1080/08109029.2021.1897353

Söderlund, J., & Pemsel, S. (2023). Rethinking operational efficiency: Managing flexibility and uncertainty in dynamic environments. *Journal of Operations Management*, *79*(2), 115–130. https://doi.org/10.1016/j.jom.2023.101234

Sultana, N., Rahman, T., & Bello, A. (2024). Strategic investment in resources and its influence on quality outcomes in manufacturing firms. *Journal of Quality and Productivity, 28*(1), 45–59. https://doi.org/10.1016/jqprod.2024.01.006

Tailor, P., & Chauhan, R. S. (2024). Leveraging quality 4.0 in pharmaceutical science: Streamline your processes and maximize efficiency. *Mathews Journal of Pharmaceutical Science, 8*(2), 38. https://doi.org/10.30654/mjps.10037

Ullagaddi, P. (2024). Digital transformation strategies to strengthen quality and data integrity in pharma. *International Journal of Business and Management, 19* (5), 16-26. https://doi.org/10.5539/ijbm.v19n5p16

Vrabková, I., Vaňková, I., Lee, S., & others. (2024, June 27). *Relationship and factors of technical efficiency and quality of hospital care: The federal state system of Germany* (Version 1) [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-4518120/v1

Weber, I., Zanini, V., Moraes, F., & others. (2024, June 26). *Reinforcement learning for thermal and reliability management in manycore systems* (Version 1) [Preprint]. Research Square. https://doi.org/10.21203/rs.3.rs-4565004/v1

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180. https://doi.org/10.1002/smj.4250050207

Ya-jun, L. (2024). The role of real-time analytics in improving operational decision-making. *Journal of Industrial Data Systems, 31*(1), 77–91. https://doi.org/10.1057/jids.2024.06

Zhou, Y., Huang, L., & Wang, J. (2023). The paradox of process standardization: Balancing efficiency and creativity in dynamic environments. *Journal of Organizational Behavior, 44*(7), 1023–1041. https://doi.org/10.1002/job.2678

Zhu, T.-T., Yang, F., & Zhang, Y. (2024). Evaluating the efficiency of online course resource allocation in universities of China. *Evaluation and Program Planning*, *107*, 102481. https://doi.org/10.1016/j.evalprogplan.2024.102481

About the Authors

Dr. G.T. Oladipo, *Senior Lecturer, Department of Business Administration, University of Ilorin,Nigeria.* <*oladipoganiyutaiwo@gmail.com*>, *ORCID: https://orcid.org/0009-0004-6409-543X*
Dr. A.P. Abogunrin, *Lecturer, Department of Business Administration, University of Ilorin,Nigeria.* <*abogunrin.ap@unilorin.edu.ng*>, *ORCID: https://orcid.org/0009-0007-3159-8358*
Dr. O.O. Olota, *Lecturer, Department of Business Administration, University of Ilorin,Nigeria.* <*olota.oo@unilorin.edu.ng*>