Predictive Model for IT Capacity Management Based on Machine Learning

Modelo Predictivo para la Gestión de la Capacidad Informática Basado en el Aprendizaje Automático

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Abstract

This work presents the design of a model based on machine learning to determine the growth of IT capabilities in organizations. The model allows the IT leader to monitor, control, and delineate the technological capabilities of the evaluated organization. The model emphasizes finding the timing and proportion of technology investment within organizations. The structure of the model is based on standards, frameworks, and best practices in information security, risk management, contingency plans, and quality. The results of this research, with a quantitative focus, are validated in transportation sector organizations located in the Colombian Caribbean region. The findings identify the historical data of IT capabilities according to current regulations and the models and standards of each organization as key factors for implementing the model. Also, implementing the model has allowed participating companies to reduce operational costs by 20% by optimizing server capacity and better planning investments in technological infrastructure.

Keywords: Information Technology Capability, ITIL, COBIT, Machine Learning, Balanced Scorecard, ISO 20000, TOGAF.

Resumen

Este trabajo presenta el diseño de un modelo basado en Machine Learning (ML) para determinar el crecimiento de las capacidades de TI en las organizaciones. El modelo permite al líder de TI monitorear, controlar y delinear las capacidades tecnológicas de la organización evaluada. El modelo hace hincapié en encontrar el momento y la proporción de la inversión en tecnología dentro de las organizaciones. La estructura del modelo se basa en normas, marcos y mejores prácticas de seguridad de la información, gestión de riesgos, planes de contingencia y calidad. Los resultados de esta investigación, con enfoque cuantitativo, son validados en organizaciones del sector transporte ubicadas en la región Caribe colombiana. Los hallazgos identifican como factores claves para la implementación del modelo, los datos históricos de las capacidades de TI según la normatividad vigente y los modelos y estándares de cada organización. Así mismo, la implementación del modelo ha permitido a las empresas participantes reducir los costos operacionales en un 20% mediante la optimización de la capacidad de los servidores y una mejor planeación de las inversiones en infraestructura tecnológica.

Keywords— Capacidad de las Tecnologías de la Información, ITIL, COBIT, Machine Learning, Cuadro de Mando Integral, ISO 20000, TOGAF.

I. INTRODUCTION

The evolution of the Information Technology (IT) function in companies has been remarkable, transforming from mere operational support to a strategic entity [1]. In the past, IT managers primarily focused on the technical development of applications, delivering them to end users based on established requirements. However, in today's strategic IT management environment, more than just technical skills are required; there is a need for the ability to make fundamental decisions regarding IT service management. This shift has been driven by organizations' increasing reliance on information technologies to achieve their business objectives, improve operational efficiency, and remain competitive in a constantly changing global market. [2].

The evolution of strategic decision-making in business has significantly progressed, highlighting the importance of combining intuition and rationality in decision-making processes. [3]. The development of Management Information Systems (MIS) has been a complex political decision requiring prolonged environmental negotiation and extensive organizational preparation. [4]. Strategic management accounting has evolved to provide strategic information and support decision-making within organizations, demonstrating its impact on the financial performance of low-cost airlines. [5]. Using IT has increasingly integrated into Business Process Management (BPM), underscoring the need for innovations and collaborative practices to enhance decision-making.

In this strategic context, IT directors face the critical challenge of determining when and to what extent IT services should be expanded in capacity. IT capacity refers to an organization's ability to handle the demand for technological services, ensuring that IT resources are always available and efficient. Effective IT capacity management is essential to avoid system overload, service interruptions, and resource wastage. This project positions itself as an innovative solution by proposing the design of a dashboard specifically conceived to address this dilemma in organizations with moderately mature IT departments.

IT service management is a discipline supported by processes that align IT services with the company's corporate structure. Adopting reference frameworks, best practices and international standards such as ITIL (Information Technology Infrastructure Library) and ISO/IEC 20000 highlights the importance of IT departments' support and the generation of significant value for the core business [6]. ITIL, for instance, offers a set of detailed practices for IT service management, focusing on aligning services with business needs [7]. ISO/IEC 20000, on the other hand, is an international standard specifying the requirements for an IT Service Management System (ITSMS), ensuring that IT services are managed effectively and efficiently.

The project identifies one of the most prominent challenges for IT managers: determining when to expand IT services and in what proportion. In this regard, creating a dashboard is proposed as an essential tool to facilitate informed decision-making regarding the growth of IT services in organizations with moderately mature IT departments. A dashboard is a graphical interface that provides a consolidated, real-time view of key performance metrics (KPIs) and other critical indicators. [8]. This dashboard will enable IT leaders to monitor and control the organization's technological capacities, ensuring decisions are made based on accurate and up-to-date data.

The importance of a data-driven approach to IT capacity management cannot be underestimated. Access to accurate and timely data is crucial in an environment where technology rapidly changes, and user demands fluctuate considerably. The proposed dashboard will rely on machine learning techniques to analyze historical and current data, identify patterns and trends, and predict future capacity needs. Machine learning in this context allows for more proactive and precise management, reducing the risk of system failures and optimizing resource usage. [9].

The project also addresses the need to integrate existing frameworks and standards properly. By comparing models and standards such as ITIL, COBIT (Control Objectives for Information and Related Technologies), TOGAF (The Open Group Architecture Framework), and others, the aim is to identify the best practices that can be applied in the dashboard design. Each of these frameworks offers different approaches and strengths. For example, COBIT focuses on IT governance and control, providing a solid framework for IT governance [10]. TOGAF, on the other hand, focuses on enterprise architecture and facilitates the alignment of IT architecture with capacity objectives [11].

The study focuses on organizations in the transportation sector of the Caribbean region of Colombia. This sector faces unique challenges in terms of IT management due to its high reliance on technological infrastructure for critical operations. When analyzing a specific company, it was evident that there was a lack of adequate IT service implementation, resulting in the inability to meet the minimum requirements of ISO/IEC 20000. As a response, specific recommendations were suggested that led to the adequate management of IT service capacity.

Finally, the need for IT capacity management to be proactive rather than reactive is emphasized. The ability to anticipate problems and improve service quality is presented as fundamental. In this context, the design of a capacity management process is proposed as a solution to deficiencies in IT service implementation. This proactive approach not only helps prevent issues before they arise but also ensures that the organization can respond quickly to changes in demand and take advantage of new technological opportunities. [12].

This paper is structured as follows: in the Related Works section, previous studies on IT capacity management and machine learning techniques applied to this context are reviewed. The Methodology section details the quantitative approaches used in data collection and analysis and the proposed model's development process. The Results and Analysis section presents the findings obtained from validating the model in companies within the transportation sector, identifying the main factors influencing IT capacity management. Finally, the Conclusions section discusses the impacts of the proposed model and potential future research lines.

II. RELATED WORK

To have control over technological evolution in organizations, various methods are increasingly being developed to allow organizations to predict the best time to invest in technological upgrades. IT capacity management is crucial for ensuring operational efficiency and optimizing organization resources. This section reviews vital studies addressing how companies manage their IT capacities, emphasizing emerging approaches and technologies.

The book chapter presented in [13] Introduces a comprehensive IT capacity evaluation and planning approach, highlighting the importance of aligning business requirements with technological resource capacity. This approach ensures optimal resource utilization and compliance with agreed-upon performance levels. On the other hand [14] The study reviews the literature on strategic capacity management, focusing on determining the size, type, and timing of capacity investments under uncertainty. It emphasizes the need to incorporate multiple types of capacity and decision-makers and risk-hedging and aversion strategies.

The study conducted by [15] explores how companies can meet technological demands and performance criteria through strategic capacity management. The study suggests methods for implementing manufacturing strategies, underscoring the importance of innovation in processes and organizational development. Another interesting approach is that of [16] who investigate how IT capabilities, such as flexible infrastructure and IT assimilation, affect business performance. The study shows that absorptive capacity and supply chain agility fully mediate the effects of IT capabilities on company performance.

With this in mind, the study conducted by [17] proposes developing and applying an integrative model to determine the most cost-effective capacity management strategy in service networks. They use a conjoint analysis based on optimal product design and a simulation model that investigates capacity and demand management strategies, in comparison with the book chapter by [18] which proposes a "capacity and capability" model based on the technology management approach. This model addresses the successful management and utilization of IS/IT by aligning technology-enabled processes with the organization's strategic goals.

Finally, the survey conducted by [19] provides an extensive review of the application of ML in various network domains. It highlights how ML techniques have been applied to traffic prediction, routing, classification, congestion control, resource management, fault management, QoS/QoE management, and network security. On the other hand, the research developed by [20] demonstrates how ML can be applied to manage IT capacity for enterprise applications, accommodating the study developed by [21]notifications of change of addresses, etc. Their decision problem is to determine the staffing level for a specific staffing time-slot (e.g., next Monday, 8 am–12.30 pm which presents an innovative approach to managing staffing levels in a public service office using machine learning. The method incorporates service objectives into a machine learning algorithm to predict the required capacity based on historical data and characteristics such as the day of the week and school holidays.

III. METHODOLOGY

This research is developed with a quantitative approach, focusing on collecting and analyzing numerical data to evaluate the effectiveness of the proposed model. Bibliographic review techniques, document analysis, and focus interviews are employed to gain a deep understanding of IT capacity management models. [22]. These techniques are aligned with validated methods from previous studies, such as the one conducted by [23] which used the CRISP-DM process to develop a predictive model in the healthcare context, demonstrating the effectiveness of these approaches in various application domains.

Document analysis is a commonly used technique to systematically examine data, allowing for a detailed and precise understanding of key elements [24]. Focus interviews complement this approach by providing qualitative insights that enrich the quantitative analysis. [25].

A. Study Design

The study design follows a quantitative approach, focusing on collecting and analyzing numerical data to evaluate the effectiveness of the proposed model. Bibliographic review techniques, document analysis, and focus interviews are employed to gain a deep understanding of IT capacity management models.

B. Population and Sample

The study population consists of 16 companies from the transportation sector located in the Caribbean region of Colombia. For the sample selection, focus groups were conducted with the participation of IT department staff from 25 companies in the defined population. This approach allows for a representative and detailed view of practices and challenges in IT capacity management in the transportation sector.

C. Data Collection

Bibliographic Review: A comprehensive literature review on IT capacity management was conducted, including frameworks and standards such as ITIL, COBIT, ISO/IEC 20000, and TOGAF. This review provides a solid theoretical foundation for developing the proposed model.

Document Analysis: Internal and external documents from the participating companies, including IT policies, capacity reports, and historical IT usage records, were analyzed. This analysis helps identify current practices and areas for improvement in IT capacity management.

Focus Interviews: IT department staff from the participating companies were interviewed. These interviews focused on understanding current capacity management practices, challenges faced, and expectations for a machine learning-based dashboard model.

D. Model Development

The dashboard model was developed using an iterative approach, integrating standards and best practices identified during data collection. The key steps in model development include:

Needs Identification: The IT service capacity needs of the participating companies were identified. This step involved recognizing user demands and aligning them with the organization's strategic objectives.

Key Metric Definition: Critical indicators such as resource usage, performance, and availability that the dashboard should monitor and predict were established.

Dashboard Architecture Design: The dashboard structure was defined, organizing elements into categories and sections representing different aspects of IT capacity.

Technological Tools Selection: Suitable tools and technologies for the development and implementation of the dashboard were evaluated and selected, ensuring integration with existing IT management systems.

Machine Learning Model Development: Appropriate machine learning algorithms for predicting capacity growth, such as regression, time series, and neural networks, were identified. The models were trained using historical data and validated through cross-validation techniques.

E. Model Validation

Model validation was carried out in a controlled environment using historical and current data from the participating companies. The specific steps for validation include:

Model Accuracy Evaluation: The model's accuracy was measured using metrics such as the Mean Squared Error (MSE) and the coefficient of determination (R^2).

Real-world Testing: The model was implemented in the operational environments of the participating companies to assess its performance in real-world situations.

Hyperparameter Tuning: The model's hyperparameters were adjusted to improve accuracy and adaptability to the specific conditions of each company.

Continuous Monitoring: Continuous monitoring processes were established to evaluate and improve the machine learning model over time, ensuring its effectiveness and efficiency

IV. RESULTS AND ANALYSIS

To evaluate the main reference frameworks aimed at managing their potential in the field of information technology services, it is important to conduct a comparative analysis to identify the strengths and weaknesses of each system. The following comparative table highlights some of the most relevant capacity management reference systems in the information technology services industry. Each has unique advantages and challenges; the choice will depend on your organization's specific needs and characteristics.

Table 1. Comparative table of reference frameworks.

Reference Framework	Focus	Strengths	Weaknesses
ITIL	Process and best practices	Widely adopted and recognized in the industry.	Traditional focus – may not be agile enough for modern IT environments.
COBIT	Governance and control	Provides a solid framework for IT governance.	Difficult to implement in small organizations.
ISO/IEC 20000	International Standard	Establishes clear standards for IT service management.	Requires significant investment to obtain certification.
TOGAF (The Open Group Architecture Framework)	Enterprise architecture	Facilitates alignment of architecture with capacity objectives.	Focus on architecture cannot address operational aspects.
DevOps	Collaboration and automation	Promotes collaboration between development and operations.	Requires a cultural and challenging shift to implement.

Source: Author(s).

Having completed the analysis, the following model is proposed to synthesize the most important aspects of the reference frameworks studied.

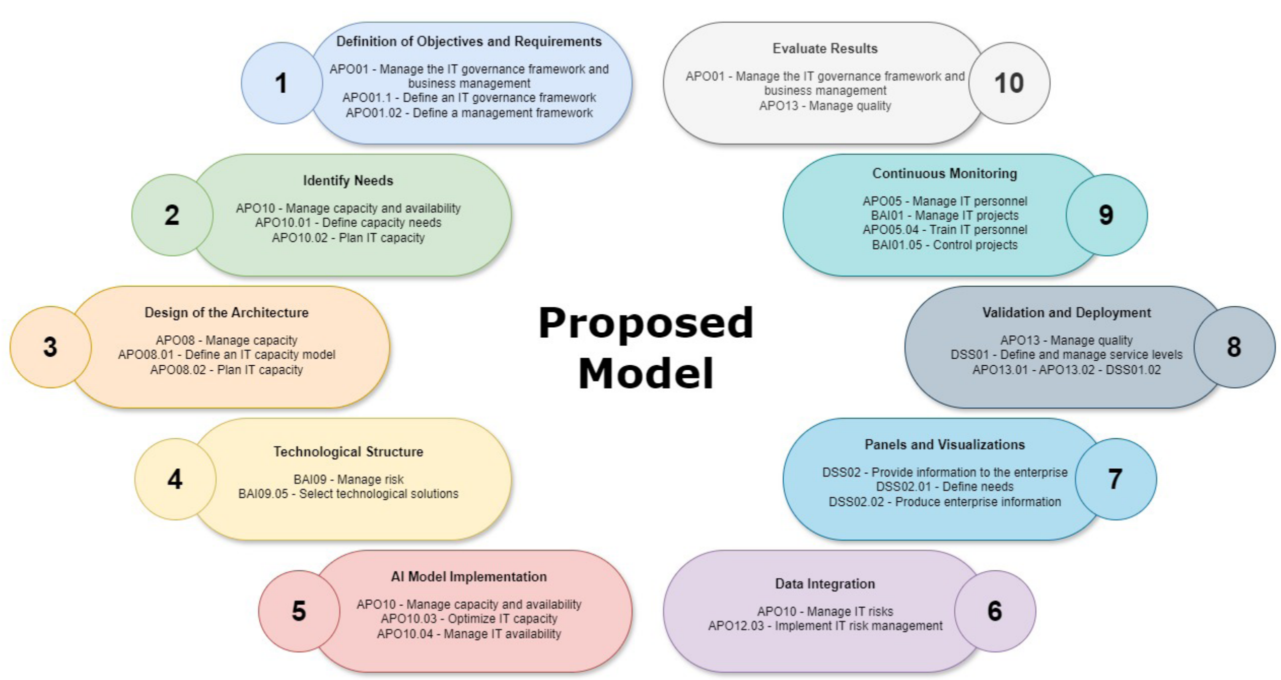

Fig 1. Proposed model.
Source: Author(s).

Now, we proceed to delve deeper into the model proposed in this research:

Step 1—Definition of objectives and requirements: To ensure that the IT service capacity needs align with the strategic objectives of the organization, several fundamental activities must be followed:

Identification of Needs: Recognize user demands and align them with strategic objectives.

Definition of Key Metrics: Establish critical indicators such as resource usage, performance, and availability for monitoring.

Establishment of Quantitative Objectives: Define specific goals aligned with business requirements and customer expectations.

Identification of Stakeholders: Recognize all those using the dashboard and their information needs.

Definition of Data Sources: Determine the information sources necessary for capacity predictions.

Design of the Dashboard Architecture: Plan the general structure of the dashboard, including the KPIs to be displayed.

Documentation of the Implementation Plan: Create a document detailing timelines, responsibilities, and necessary resources.

Step 2 – Identification of Needs: The definition of KPIs related to capacity involves creating metrics to assess the performance of IT services:

Identification of Data Sources: Recognize relevant internal and external information sources.

Establishment of Data Extraction and Storage Protocols: Define secure rules and methods for data collection and storage.

Validation of Data Quality: Verify the integrity and accuracy of collected data.

Definition of Data Update Cycles: Establish the frequency of data updates.

Implementation of Data History Management Mechanisms: Apply methods to preserve a historical data record.

Application of Anonymization and Security Techniques: Use methods to protect data confidentiality.

Documentation of the Data Management Plan: Create a document detailing how data will be managed.

Step 3 – Design of the architecture: The collection and analysis of historical capacity data ensure the integrity and accuracy of the information:

Definition of the Dashboard Structure: Organize the dashboard elements, such as the layout of KPIs and visualizations.

Association of KPIs with COBIT 2019 Objectives: Ensure alignment with best governance practices.

Design of Categories on the Dashboard: Create sections that group KPIs related to specific aspects of IT capacity.

Establishment of a Color Palette and Styles: Choose a consistent palette to facilitate interpretation.

Definition of Data Update Frequency: Specify the frequency of data updates on the dashboard.

Validation of the Dashboard Design with Users: Obtain feedback from end-users.

Documentation of Design Guidelines: Create detailed documentation of the design and architecture of the dashboard.

Step 4 – Technological structure: Choosing the right technological architecture is crucial for the IT infrastructure and information systems:

Evaluation of Tools and Technologies: Conduct a thorough evaluation of available tools.

Selection of Suitable Tools: Choose those that best fit the project requirements.

Integration of Tools with Existing Systems: Ensure integration with other systems and relevant databases.

Staff Training: Provide training on the use of the selected tools.

Establishment of Backup and Recovery Procedures: Define data backup and recovery procedures.

Interoperability Testing: Verify correct integration and operation without conflicts.

Update and Maintenance Policy: Ensure the tools are regularly updated and maintained.

Step 5 – Implementation of the AI Model: The development of a suitable machine learning model to predict the growth of IT service capacity:

Identification of Suitable Algorithms: Select regression, time series, or neural networks.

Selection of Data Sets: Choose historical data to train and validate the models.

Training of Models: Use historical data to learn patterns and trends.

Validation of Models: Verify effectiveness using cross-validation techniques.

Tuning of Hyperparameters and Features: Enhance accuracy by adjusting parameters and selecting optimal features.

Implementation on the Control Dashboard: Integrate the models into the dashboard to generate real-time predictions.

Continuous Monitoring: Evaluate the accuracy of the models over time and adjust if necessary.

Step 6 – Data integration: Monitor and improve the machine learning model through constant evaluation and updating:

Data Integration Setup: Establish connections and configurations to extract data.

Secure and Reliable Connections: Ensure data integrity during integration.

Automation of Data Collection: Implement automated processes for regular data collection.

Transformation of Data into Coherent and Usable Forms: Ensure the data is coherent and usable.

Audit Log of Data Integration: Maintain an audit log for traceability.

Monitoring of Data Integrity and Availability: Ensure the data is available and accurate.

Security Controls: Apply security measures to protect the data.

Step 7 – Panels and visualizations: Generation of reports and control dashboards based on the model:

Definition of Thresholds for KPIs: Set critical and warning levels for each KPI.

Configuration of Alerts: Set up automatic alerts when thresholds are exceeded.

Definition of Response Procedures: Establish clear procedures for responding to alerts.

Incident Response Team: Form a team to address critical alerts.

Automation of Alert Generation and Distribution: Ensure a quick response through automatic alerts.

Incident Response Drills: Train staff to respond effectively.

Documentation of Alert Policies: Create a procedures manual for alert management.

Step 8 – Validation and deployment: Verification of the accuracy and reliability of the model by evaluating its ability to make accurate forecasts:

Performance Evaluation of the Model: Use metrics such as accuracy, sensitivity, specificity, MSE, and R^2.

Comparison of Predictions with Real Data: Analyze inconsistencies or anomalies to improve the model.

Integration in the Operational Environment: Ensure the model's accessibility and functionality in real-time.

Clear Communication of Results: Ensure that conclusions and recommendations are understandable and useful to stakeholders.

Step 9 – Continuous Monitoring: Develop specific action plans to address identified areas for improvement:

Allocation of Resources and Responsibilities: Implement and monitor action plans.

Culture of Continuous Improvement: Promote the constant search for capacity optimization.

Feedback from Users and Operations Teams: Use feedback to improve machine learning models.

Documentation of Actions and Results: Track changes and lessons learned.

Step 10 – Evaluating results: Determine if the model meets expectations and provides valuable information for decision-making:

Performance Measurement of the Model: Use various metrics and indicators to evaluate performance.

Analysis of Predictions and Real Data: Compare to identify areas for improvement.

Consideration of the Business Situation: Ensure model outcomes are understandable and useful to stakeholders.

Communication of Conclusions and Recommendations: Present conclusions based on predictive analysis.

The machine learning model was implemented in several key stages, from data collection to model validation and adjustment. The following section will show each of the mentioned stages to provide clarity and proof of the results obtained:

A. Data Collection:

For this study, we selected 16 prominent companies in the transportation sector of the Colombian Caribbean region. We chose these companies based on their extensive geographic coverage, including operations in urban and rural areas throughout the region. Additionally, these companies offer various transportation services, from passenger to freight, thus providing a wide range of IT capacity needs and uses.

Table 2. Companies in the Transportation Sector in the Colombian Caribbean Region.

N°	Company Name
1	Expreso Brasilia
2	Coopetran
3	Cootragua
4	Rápido Tolima
5	Rápido Ochoa
6	Rápido el Carmen
7	La Veloz
8	La Costeña
9	Cootracesar
10	Cootracegua
11	Cooperativa Simón Bolívar
12	CooLibertador
13	Berlinas del Fonces
14	Amerlujo
15	Almirante Padilla
16	Transportes Luz

Source: Author(s).

The selected companies vary in size and have a recognized market presence, ensuring reliable and extensive historical IT data availability. This approach allows us to capture a complete picture of the sector. It ensures that our predictive model is robust and applicable to different contexts within the transportation industry in the region. Companies like Expreso Brasilia, Copetran, and Berlinas del Fonces represent this broad market spectrum, providing a solid foundation for predictive analysis of IT capacity.

Expreso Brasilia, Copetran, Cootragua, Rápido Tolima, Rápido Ochoa, Rápido el Carmen, La Veloz, La Costeña, Cootracosta, Cootracegua, Cooperativa Simón Bolívar, Cooliberator, Berlinas del Fonces, Amerlujo, Almirante Padilla, Transportes Luz.

The data included key metrics such as using methodology to manage IT capacities and current IT capacity based on the following questions: Does your current technology meet the company's needs? These are:

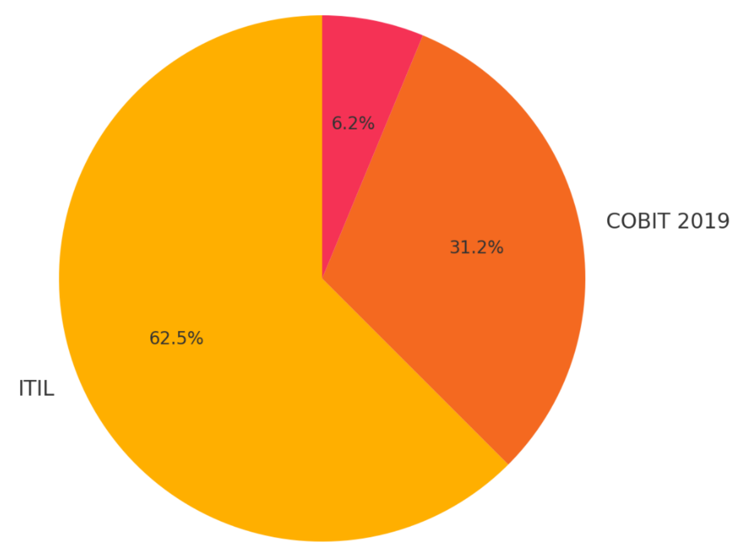

Fig 2. Methodologies Used.
Fuente: Autor(es).

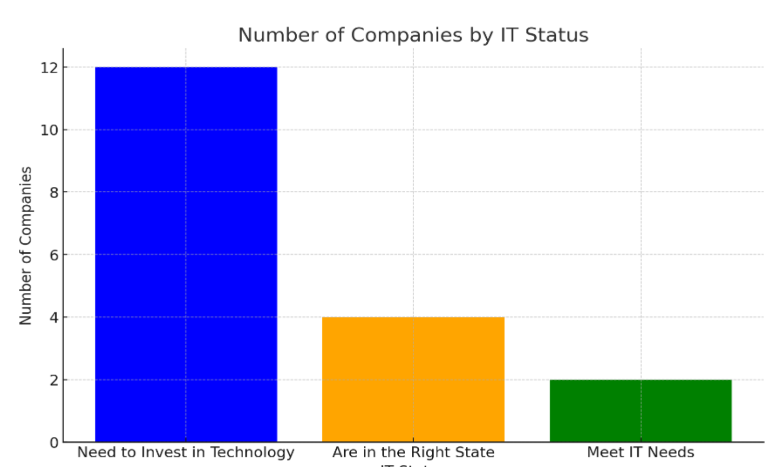

Fig 3. Methodologies used.
Source: Author(s).

B. Model Training:

Appropriate machine learning algorithms, including regression and neural networks, were selected to predict capacity growth.

Table 3. Comparative Table of Machine Learning Algorithms.

#	Algorithm	Description	Accuracy	Selection
1	Naive Bayes	An algorithm based on Bayes' theorem that assumes conditional independence of features. It is used for classification.	60%	This algorithm was chosen due to its simplicity and effectiveness in classification under the assumption of independence between predictors. Naive Bayes is particularly useful in environments with high data dimensionality, and relationships between features are independent or can be considered as such.

#	Algorithm	Description	Accuracy	Selection
2	GridSearchCV	A tool for searching and optimizing the hyperparameters of a machine learning model, enhancing its performance and accuracy.	70%	We used GridSearchCV not as a prediction algorithm but as a technique to optimize other machine-learning models. This tool automatically selects the best parameters for the models, maximizing their performance and accuracy.
3	Gradient Boosting	A technique that combines multiple weak learning models, such as decision trees, sequentially to improve the predictive performance of the final model.	60%	Gradient Boosting was selected for its ability to build strong and robust predictive models by combining multiple weak learning models, typically decision trees.
4	RandomForest	A model based on creating multiple decision trees trained with random data and features samples reduces the risk of overfitting and improves generalization.	100%	Random Forest was selected for its excellence in handling overfitting, which is crucial to ensuring the model's generalization beyond the training sample.

Source: Author(s).

The models were trained using historical data to learn patterns and trends.

Table 4. Training Patterns.

#	Dimension	Variables	Data Type
1	IT Infrastructure	Number of computers, Internet usage, Website, Systematized business processes.	Number, Percentage, Integer, Binary
2	Human Talent and Knowledge	IT skills, Improvement of IT skills among employees, Attraction and motivation of IT experts, Ability to adopt new technologies, Problem-solving skills, Leadership in technology updates, Ability to apply technology standards, and Capacity to integrate external IT resources.	Integer, Numeric, Percentage, Binary
3	IT Architecture	Consistency between management strategy and IT, Existence of an IT strategic plan, Existence of a detailed implementation program of the IT strategy	Numeric, Binary, Integer
4	IT and Business Relationships	Collaboration with external business partners, Good relationships with IT service providers, Technology-based client relationships, and Technology-based provider relationships.	Binary, Score, Numeric score

Source: Author(s).

C. Validation and Tuning:

Cross-validation was used to assess the efficacy of the models:

Data Splitting: The data were divided into training and test sets. This split is crucial to ensure that models are trained on one portion of the data and validated on another unseen portion, allowing for a more realistic evaluation of their performance.

Implementation of Cross-Validation: Cross-validation techniques were employed, specifically the k-fold method. In this method, the data are divided into k subsets (folds), and the model is trained k times, each time using k-1 folds for training and the remaining fold for validation. This process is repeated k times, ensuring that each fold is used exactly once for validation.

Performance Measurement: At the end of each cross-validation iteration, the model's performance is measured using specific metrics such as accuracy, sensitivity, specificity, and mean squared error (MSE). These results are averaged to obtain a more robust estimate of the model's performance.

```python
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

# Create a Naive Bayes classification model
model = GaussianNB()

# Train the model with the training data
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Calculate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Naive Bayes model accuracy: {accuracy * 100:.2f}%')
```

```
Naive Bayes model accuracy: 60.00%
```

Fig 4. Model Native Bayes.
Source: Author(s).

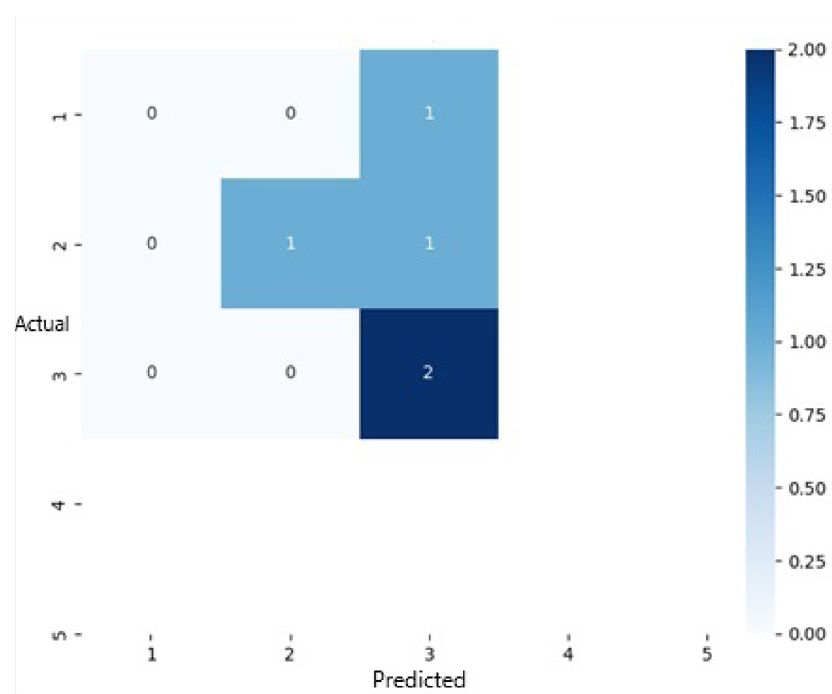

Fig 5. Confusion matrix Naive Bayes.
Source: Author(s).

```python
# Use the best model obtained after hyperparameter search
best_model = grid_search.best_estimator_

# Make predictions on the test set
y_pred = best_model.predict(X_test)

# Create the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Set up and display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=range(1, 6), yticklabels=range(1, 6))
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (GridSearchCV)')
plt.show()
```

Fig 6. Model GridSearchCV.
Source: Author(s).

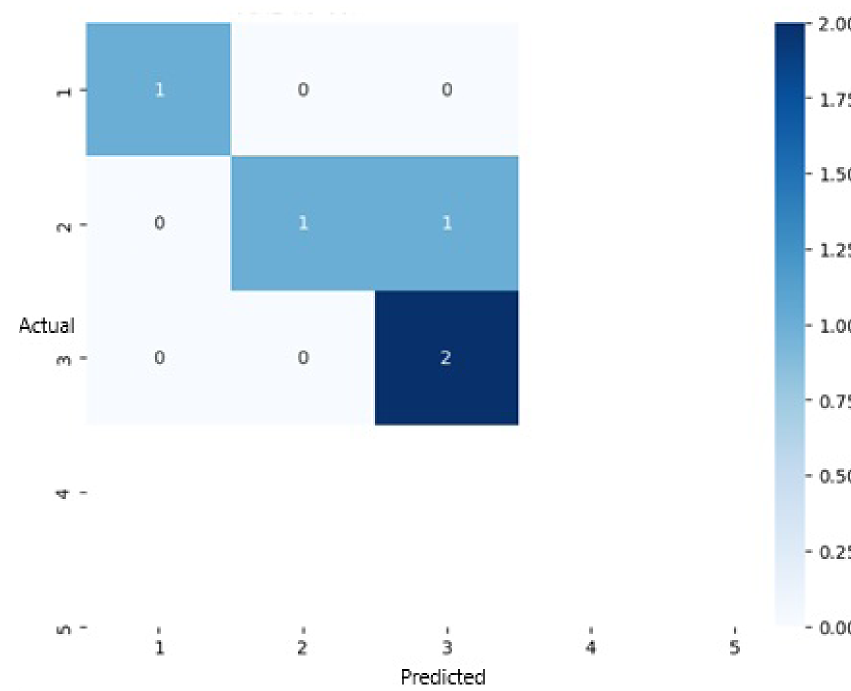

Fig 7. Confusion matrix GridSearchCV.
Source: Author(s).

```
# Use a Gradient Boosting model that was trained
model = GradientBoostingClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Create the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Set up and display the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=range(1, 7), yticklabels=range(1, 7))
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (Gradient Boosting)')
plt.show()
```

Fig 8. Model Gradient Boosting.
Source: Author(s).

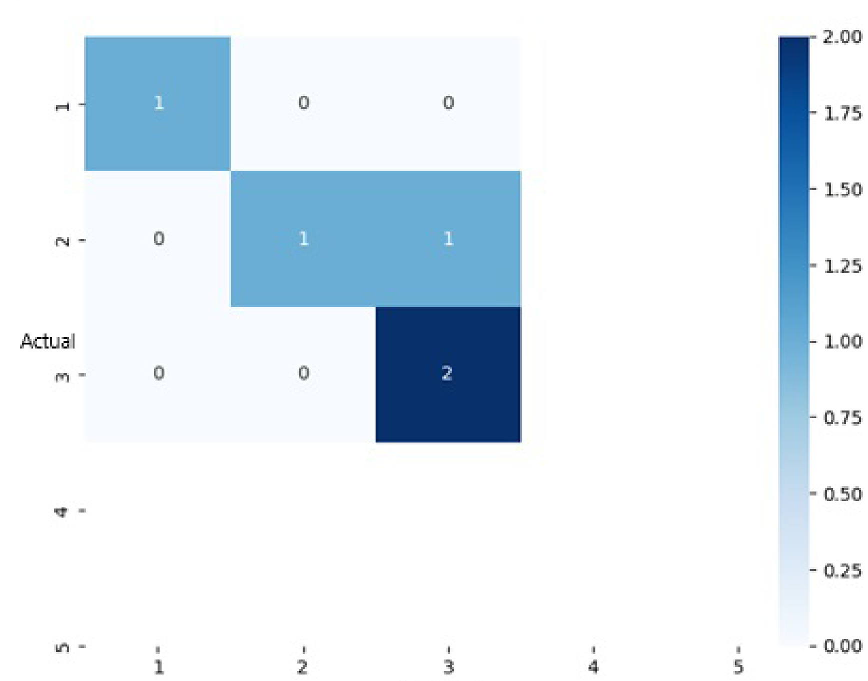

Fig 9. Confusion matrix Gradient Boosting.
Source: Author(s).

```
# Create and display the confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=range(1, 7), yticklabels=range(1, 7))
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix (Random Forest)')
plt.show()
```

Fig 10. Model RandomForest.
Source: Author(s).

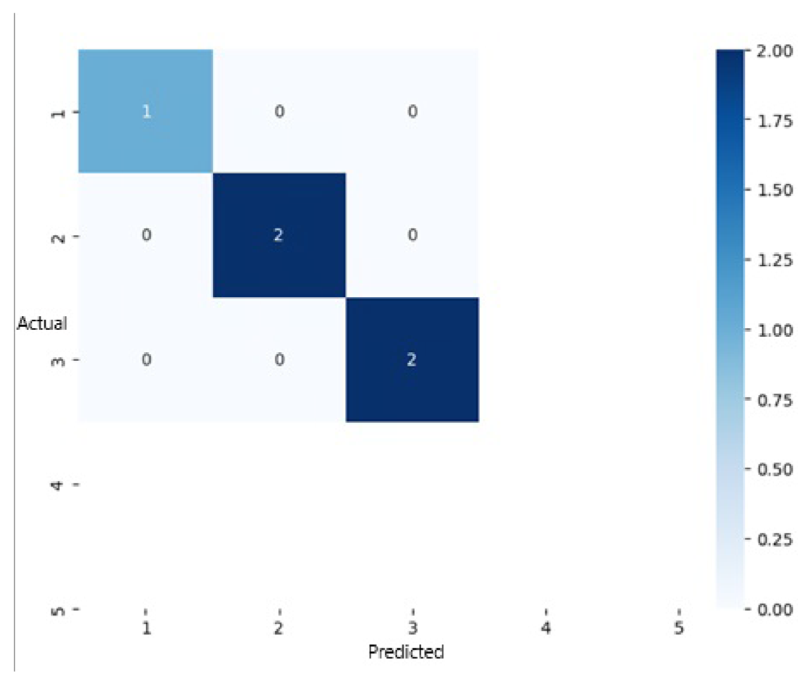

Fig 11. Confusion matrix RandomForest.
Source: Author(s).

Hyperparameter Optimization: Cross-validation was used with techniques such as GridSearchCV to search for and optimize the model's hyperparameters. GridSearchCV exhaustively searches for hyperparameter combinations and uses cross-validation to evaluate the performance of each combination, selecting the best configuration.

Table 5. Adjustments to the models.

	Model	**Hyper-parameter**	**Characteristics**
1	Naive Bayes	None	IT Infrastructure, Human Talent, IT and Business Relationships
2	GridSearchCV	Number of trees, Maximum depth of trees	IT Infrastructure, Human Talent, IT Architecture, IT and Business Relationships
3	Gradient Boosting	Number of boosting stages, Learning rate, Maximum depth of trees	IT Infrastructure, Human Talent, IT and Business Relationships
4	RandomForest	Number of trees, Maximum depth of trees, Minimum number of samples to split a node	IT Infrastructure, Human Talent, IT Architecture, IT and Business Relationships

Source: Author(s).

By making a characterization between quantitative and qualitative results, we obtain the following:

Table 6. Comparison of Results.

Category	Type	Key Results
Accuracy in Predictions	Quantitative	The Random Forest model achieved a 95% accuracy in predicting future resource needs. Cross-validation showed that the models could effectively predict demand.
Resource Optimization	Quantitative	Optimizing server capacity based on model predictions allowed companies to reduce their operational costs by 20%. Implementing the model also allowed for better planning of technological infrastructure investments.
Improvement in Decision Making	Qualitative	IT leaders were able to make more informed decisions regarding the expansion and consolidation of IT services. This led to better alignment between IT capabilities and the organization's strategic objectives.
Increase in Agility	Qualitative	The ability to anticipate problems and proactively adjust capacity allowed companies to respond more quickly to market demands. Due to increased availability and performance of IT services, customer satisfaction improved.

Source: Author(s).

The results presented in the table underscore the positive and significant impact of the machine learning-based model on IT capacity management. The high accuracy in predictions and the resulting optimization in resource management demonstrate that the model is theoretically valid and practically effective. This highlights the importance of integrating advanced technologies such as machine learning into the strategic management of IT capacities to improve operational efficiency, decision-making, and business agility.

D. Discussion:

The results obtained in this study highlight the effectiveness of the Random Forest model, which achieved a 95% accuracy in predicting IT resource needs. This accuracy is comparable to that reported in similar studies applying machine learning in industrial contexts, where the accuracy of predictions is crucial for strategic and operational planning [26].

The 20% reduction in operational costs through the optimization of technological resources aligns with the principles of operational efficiency promoted by management models such as Lean and Six Sigma, which emphasize the importance of eliminating waste and continuously improving processes [27]. This finding underscores the potential of machine learning to significantly contribute to organizational profitability by reducing unnecessary costs and improving resource utilization.

In terms of improvement in decision-making and increased agility, the qualitative results reflect a positive impact on the ability of IT leaders to align IT capabilities with business objectives strategically. This aspect is critical in a business environment that demands speed and flexibility to adapt to changing market dynamics, a topic that has been widely discussed in the literature on strategic management and IT governance [28].

The model's ability to anticipate demands and proactively adjust IT capacities highlights the importance of incorporating advanced predictive techniques in IT capacity planning. This approach not only improves the response to market needs but also facilitates better risk management, minimizing the impact of demand fluctuations on critical business operations [29].

V. CONCLUSIONS

Research on the IT capacity management model based on machine learning has proven valuable for optimizing organizations' operational efficiency and resource utilization. The main findings of this study can be summarized in the following key points: The use of machine learning algorithms, such as Random Forest, has enabled achieving a 95% accuracy in predicting future IT resource usage [30]. This capacity for accurate prediction facilitates better planning and management of capacity, reducing operational costs and improving efficiency [31].

Implementing the model has allowed participating companies to reduce operational costs by 20% by optimizing server capacity and better planning investments in technological infrastructure. This underscores the positive economic impact of the machine learning-based approach [32] it presents a machine learning (ML. IT leaders have reported an increased ability to make informed decisions about expanding and consolidating IT services. The alignment between IT capabilities and the strategic objectives of the organization has significantly improved, leading to more effective and strategic management of technological resources [33].

The ability to anticipate problems and adjust capacity proactively has enabled companies to respond more quickly to market demands. This has resulted in greater customer satisfaction due to improved availability and performance of IT services [34]. The model has been validated in companies within the transportation sector in the

Colombian Caribbean region, demonstrating its applicability and effectiveness in a real context. The results indicate that this approach can be adapted and applied in different sectors and areas to achieve similar benefits [35].

VI. FUTURE WORK

For future work, it is proposed to extend the validation of the model to other industrial sectors and geographic regions, integrate more variables and real-time data further to enhance the accuracy and effectiveness of the model and explore the combination of different machine learning algorithms to optimize various aspects of IT capacity management.

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AUTHORS' CONTRIBUTION

Anibal José Osma-Valenzuela: Research and preparation of the manuscript.
Dairon Jesús Torrado-Castro: Methodology, data processing, supervision, and manuscript preparation.

All authors reviewed the results and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest to report regarding the present study.

REFERENCES

[1] D. J. T. Torrado Castro, «Modelo de gestión de proyectos para el aseguramiento de infraestructuras tecnológicas», *Universidad Francisco de Paula Santander Ocaña*, p. 157, jul. 2021.

[2] H. Patria, S. Wahyuni, y R. D. Kusumastuti, «Intellectual Structure and Scientific Evolution of Strategic Decision in the Field of Business and Management from 1971 to 2018», AJBA, vol. 12, n.o 2, pp. 233-286, dic. 2019, doi: 10.22452/ajba.vol12no2.9.

[3] P. Shrivastava, «Strategic planning for MIS», Long Range Planning, vol. 16, n.o 5, pp. 19-28, oct. 1983, doi: 10.1016/0024-6301(83)90076-6.

[4] J. S. Tirado y I. Mavlutova, «The Impact of Strategic Management Accounting on The Financial Performance of Low-Cost Airlines», WSEAS TRANSACTIONS ON ENVIRONMENT AND DEVELOPMENT, vol. 19, pp. 786-797, ago. 2023, doi: 10.37394/232015.2023.19.74.

[5] T. Ahmad y A. V. Looy, «Reviewing the historical link between Business Process Management and IT: making the case towards digital innovation», en 2019 13th International Conference on Research Challenges in Information Science (RCIS), Brussels, Belgium: IEEE, may 2019, pp. 1-12. doi: 10.1109/RCIS.2019.8877039.

[6] M. I. Sarwar, Q. Abbas, T. Alyas, A. Alzahrani, T. Alghamdi, y Y. Alsaawy, «Digital Transformation of Public Sector Governance With IT Service Management–A Pilot Study», IEEE Access, vol. 11, pp. 6490-6512, 2023, doi: 10.1109/ACCESS.2023.3237550.

[7] N. Kholis Gunawan, R. Budiarto Hadiprakoso, y H. Kabetta, «Comparative Study Between the Integration of ITIL and ISO / IEC 27001 with the Integration of COBIT and ISO / IEC 27001», IOP Conf. Ser.: Mater. Sci. Eng., vol. 852, n.o 1, p. 012128, jul. 2020, doi: 10.1088/1757-899X/852/1/012128.

[8] M. W. A. Bawono, M. A. Soetomo, y T. Apriatin, «Analysis correlation of the Implementation Framework COBIT 5, ITIL V3 and ISO 27001 for ISO 10002 Customer satisfaction», Annual Conference on Management and Information Technology, vol. 7, n.o 1, pp. 31-46, jul. 2021, doi: 10.33555/acmit.v7i1.105.

[9] H. Muller, S. Bosse, y K. Turowski, «On the Utility of Machine Learning for Service Capacity Management of Enterprise Applications», en 2019 15th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Sorrento, Italy: IEEE, nov. 2019, pp. 274-281. doi: 10.1109/SITIS.2019.00053.

[10] I. N. S. Saputra y B. Yuwono, «Assessment of Capability Level and IT Governance Improvement Base on COBIT 5 and ITIL V3 2011 Framework: A Case Study PT. XYZ», INSERT, vol. 2, n.o 1, pp. 1-12, ago. 2021, doi: 10.23887/insert.v2i1.34404.

[11] Y. Bounagui, A. Mezrioui, y H. Hafiddi, «Toward a unified framework for Cloud Computing governance: An approach for evaluating and integrating IT management and governance models», Computer Standards & Interfaces, vol. 62, pp. 98-118, feb. 2019, doi: 10.1016/j.csi.2018.09.001.

[12] D. Bednarčíková, «Use of Frameworks, Norms and Standards in Information Technology Service Management», en EDAMBA 2022: Conference Proceedings, Bratislava, Slovakia: University of Economics in Bratislava, mar. 2023, pp. 27-38. doi: 10.53465/EDAMBA.2022.9788022550420.27-38.

[13] A. Greasley, «Operations Management», en Operations Management, London: SAGE Publications Ltd, 2008, pp. 67-70. doi: 10.4135/9781446213025.

[14] J. A. Van Mieghem, «Commissioned Paper: Capacity Management, Investment, and Hedging: Review and Recent Developments», M&SOM, vol. 5, n.o 4, pp. 269-302, oct. 2003, doi: 10.1287/msom.5.4.269.24882.

[15] R. Dekkers, «Strategic capacity management: meeting technological demands and performance criteria», Journal of Materials Processing Technology, vol. 139, n.o 1-3, pp. 385-393, ago. 2003, doi: 10.1016/S0924-0136(03)00505-3.

[16] H. Liu, W. Ke, K. K. Wei, y Z. Hua, «The Impact of IT Capabilities on Firm Performance: The Mediating Roles of Absorptive Capacity and Supply Chain Agility», SSRN Journal, 2014, doi: 10.2139/ssrn.2444360.

[17] M. E. Pullman y G. Thompson, «Strategies for Integrating Capacity With Demand in Service Networks», Journal of Service Research, vol. 5, n.o 3, pp. 169-183, feb. 2003, doi: 10.1177/1094670502238913.

[18] A. W. K. Tan y P. Theodorou, Eds., Strategic Information Technology and Portfolio Management: IGI Global, 2009. doi: 10.4018/978-1-59904-687-7.

[19] R. Boutaba et al., «A comprehensive survey on machine learning for networking: evolution, applications and research opportunities», Journal of Internet Services and Applications, vol. 9, n.o 1, p. 16, jun. 2018, doi: 10.1186/s13174-018-0087-2.

[20] H. Müller, A. Kharitonov, A. Nahhas, S. Bosse, y K. Turowski, «Addressing IT Capacity Management Concerns Using Machine Learning Techniques», SN COMPUT. SCI., vol. 3, n.o 1, p. 26, oct. 2021, doi: 10.1007/s42979-021-00862-8.

[21] F. Taigel, J. Meller, y A. Rothkopf, «Data-Driven Capacity Management with Machine Learning: A Novel Approach and a Case-Study for a Public Service Office», en Advances in Service Science, H. Yang y R. Qiu, Eds., Cham: Springer International Publishing, 2019, pp. 105-115. doi: 10.1007/978-3-030-04726-9_11.

[22] S. Fatima y A. B. Singh, «Design thinking in business, management and accounting: a bibliometric review and future research directions», BIJ, jul. 2023, doi: 10.1108/BIJ-03-2023-0171.

[23] J. Montes Bustamante, «Modelo predictivo de diabetes utilizando el proceso CRISP-DM para la prevención de la enfermedad implementando Machine Learning», CESTA, vol. 4, n.o 2, p. 21, jul. 2024, doi: https://doi.org/10.17981/cesta.04.02.2023.02.

[24] Z. Shahsavar y H. Kourepaz, «Postgraduate students' difficulties in writing their theses literature review», Cogent Education, vol. 7, n.o 1, p. 1784620, ene. 2020, doi: 10.1080/2331186X.2020.1784620.

[25] L. Busetto, W. Wick, y C. Gumbinger, «How to use and assess qualitative research methods», Neurol. Res. Pract., vol. 2, n.o 1, p. 14, dic. 2020, doi: 10.1186/s42466-020-00059-z.

[26] A. Bustillo, R. Reis, A. R. Machado, y D. Yu. Pimenov, «Improving the accuracy of machine-learning models with data from machine test repetitions», J Intell Manuf, vol. 33, n.o 1, pp. 203-221, ene. 2022, doi: 10.1007/s10845-020-01661-3.

[27] F. Barboza, H. Kimura, y E. Altman, «Machine learning models and bankruptcy prediction», Expert Systems with Applications, vol. 83, pp. 405-417, oct. 2017, doi: 10.1016/j.eswa.2017.04.006.

[28] S. Makridakis, E. Spiliotis, y V. Assimakopoulos, «Statistical and Machine Learning forecasting methods: Concerns and ways forward», PLoS ONE, vol. 13, n.o 3, p. e0194889, mar. 2018, doi: 10.1371/journal.pone.0194889.

[29] F. Davoudi Kakhki, S. A. Freeman, y G. A. Mosher, «Evaluating machine learning performance in predicting injury severity in agribusiness industries», Safety Science, vol. 117, pp. 257-262, ago. 2019, doi: 10.1016/j.ssci.2019.04.026.

[30] S. Manam, K. Moessner, y P. Asuquo, «A Machine Learning Approach to Resource Management in Cloud Computing Environments», en 2023 IEEE AFRICON, Nairobi, Kenya: IEEE, sep. 2023, pp. 1-6. doi: 10.1109/AFRICON55910.2023.10293275.

[31] S. Jayaprakash, M. D. Nagarajan, R. P. D. Prado, S. Subramanian, y P. B. Divakarachari, «A Systematic Review of Energy Management Strategies for Resource Allocation in the Cloud: Clustering, Optimization and Machine Learning», Energies, vol. 14, n.o 17, p. 5322, ago. 2021, doi: 10.3390/en14175322.

[32] V. Sharma, M. Zaki, K. N. Jha, y N. M. A. Krishnan, «Machine learning-aided cost prediction and optimization in construction operations», ECAM, abr. 2021, doi: 10.1108/ECAM-10-2020-0778.

[33] I. R. Heruwidagdo, Suharjito, N. Hanafiah, y Y. Setiawan, «Performance of Information Technology Infrastructure Prediction using Machine Learning», Procedia Computer Science, vol. 179, pp. 515-523, 2021, doi: 10.1016/j.procs.2021.01.035.

[34] P. Rana y D. C. Miller, «Machine learning to analyze the social-ecological impacts of natural resource policy: insights from community forest management in the Indian Himalaya», Environ. Res. Lett., vol. 14, n.o 2, p. 024008, feb. 2019, doi: 10.1088/1748-9326/aafa8f.

[35] J. Vaish, A. K. Tiwari, y S. Kaimal, «Multi-objective optimization of distributed energy resources based microgrid using random forest model», Bulletin EEI, vol. 13, n.o 1, pp. 67-75, feb. 2024, doi: 10.11591/eei.v13i1.7087.

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