



IDENTIFICATION OF PATTERNS FOR TECHNOLOGICAL INCIDENT MANAGEMENT IN A TELECOMMUNICATIONS COMPANY, PERIOD 2021–2024

Angel Ivan Torres Quijije*¹, Anthony Jahir López Coello²,
Diego Fernando Intriago Rodriguez³ and Emilio Rodrigo Zhuma Mera⁴

^{1, 2, 3, 4}Faculty of Computer Science, State Technical University of Quevedo (UTEQ), Quevedo, Ecuador.

¹<https://orcid.org/0000-0002-7037-7191>^{id}, ²<https://orcid.org/0000-0001-9779-1053>^{id}

³<https://orcid.org/0000-0003-4829-0089>^{id}, ⁴<https://orcid.org/0000-0002-3086-1413>^{id}

E-mail: *atorres@uteq.edu.ec, anthony.lopez2015@uteq.edu.ec, dintriagor3@uteq.edu.ec, ezhuma@uteq.edu.ec.

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ABSTRACT

Technological incidents represent a critical challenge for telecommunications companies due to their direct impact on service availability, customer satisfaction, and operational continuity. This study analyzes frequent patterns of technological incidents reported by a telecommunications company in Ecuador during the period 2021–2024, with the aim of supporting incident management through a data-driven approach aligned with ITIL v4. A total of 36,878 historical incident records were analyzed using data science techniques, including exploratory data analysis, normalization, value imputation, and correlation analysis. Subsequently, unsupervised data mining algorithms (Apriori, FP-Growth, and ECLAT) were applied to identify recurrent incident patterns. The results reveal significant concentrations of incidents associated with service degradation and failures in customer-end equipment, with higher incidence in specific geographic areas. Based on these patterns, an incident management reference framework composed of eight components is proposed, adapted to the operational needs of the company and aligned with ITIL v4 practices. The proposed framework facilitates incident prioritization and decision-making in IT service management, contributing to continuous improvement supported by empirical evidence.



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I. INTRODUCTION

Technological incident management is an essential component for ensuring service continuity and operational quality in telecommunications companies [1], [2]. The increasing complexity of network infrastructures, together with the growing demand for digital services, has led to a rise in the frequency and diversity of technical incidents, generating direct impacts on service availability, customer satisfaction, and organizational reputation [3]. In recent years, the telecommunications company analyzed has experienced a sustained increase in the number of reported technological incidents, reflected in longer resolution times, recurrent service degradations, and operational risks associated with the infrastructure [4]. Although reference frameworks such as the Information Technology Infrastructure Library (ITIL) provide guidelines for incident management, their effective application requires a deep understanding of the real behavior of incidents in specific organizational contexts [5], [6]. From this perspective, the present study addresses the following research problem: how can frequent patterns of technological incidents, identified from real historical data, support incident management in a telecommunications company under the guidelines of ITIL v4? To answer this question, data science techniques and frequent pattern mining are applied to historical incident records, with the aim of identifying relevant regularities and translating them into operational knowledge. The main contribution of this work is twofold. From a practical standpoint, recurrent patterns of technological incidents are identified, enabling a better understanding of frequent causes and contexts of service disruption. From a theoretical standpoint, a management reference framework aligned with ITIL v4 is proposed, built from real data and capable of being replicated or adapted in other organizations within the sector [7].

II. MATERIALS AND METHODS

II.1 DATASET

The study is based on a historical dataset of technological incidents recorded by a telecommunications company in Ecuador during the 2021–2024 period, comprising 22 variables and 36,878 records.

II.2 VARIABLE IDENTIFICATION AND EXPLORATORY ANALYSIS

The identification and categorization of variables made it possible to classify the dataset attributes into categorical, nominal, ordinal, numerical, temporal, and geographical variables [8], [9]. An exploratory data analysis (EDA) was conducted to understand the structure, distribution, and quality of the records [10], [11].

II.3 VARIABLE NORMALIZATION AND VALUE IMPUTATION

The normalization applied to categorical variables helped avoid ambiguities in model interpretation [8]. Techniques such as case folding were used to standardize labels and prepare the data for subsequent processing [9], [10]. Controlled imputation techniques were applied, including imputation based on external sources and mode imputation, to address missing or anomalous values detected in categorical variables that could affect model interpretation [10], [11].

II.4 VARIABLE CORRELATION ANALYSIS

Cramér's V measure was employed to identify collinearities and uncover associations among categorical variables through a correlation matrix [12].

II.5 DATA MINING, MODELS, AND ANALYSIS METRICS

The data mining process follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, due to its business-oriented approach and its suitability for the context of the telecommunications company analyzed [13], [14]. Unsupervised association rule mining algorithms (Apriori, FP-Growth, and ECLAT) were applied, selected for their ability to extract regularities from large datasets [15]. Evaluation metrics include support, confidence, and lift, used to determine relevance, reliability, and statistical independence [16].

III. RESULTS AND DISCUSSIONS

III.1 DATASET PREPARATION AND PREPROCESSING

Exploratory analysis made it possible to identify common challenges associated with this type of data, particularly null values, empty fields, and semantic inconsistencies in certain variables [17]. Figure 1 shows the percentage of null and empty values for each variable, revealing that three attributes exhibited lower-than-expected levels of completeness: “affected_services” (2.13%), “sector” (1.80%), and “service” (1.43%). Although these percentages are relatively low, imputation techniques were applied to ensure data consistency and support subsequent analyses.

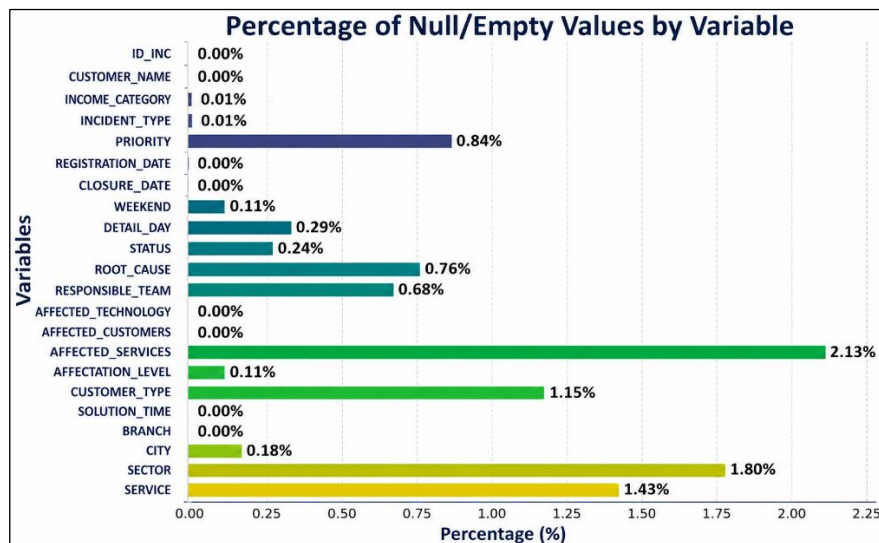


Figure 1: Null/empty values by variable.
Source: Authors, (2026).

III.2 NORMALIZATION OF CATEGORICAL VARIABLES

Categorical variables were normalized using syntactic and semantic criteria while preserving the specificity of each attribute. Standardization included the adoption of the snake_case format and the semantic unification of labels, as summarized in table 1.

Table 1: Normalization of variables related to technological incidents (preview).

Original variable	Normalized variable	Applied change
CUSTOMER_NAME	Customer_Name	Format (snake_case)
INCIDENT_TYPE	Incident_Type	Format (snake_case)
REGISTRATION_DATE	Registration_Date	Format (snake_case)
ROOT_CAUSE	Root_Cause	Format (snake_case)
BRANCH	Branch	Format

Source: Authors, (2026).

III.3 VALUE IMPUTATION

For variables with a higher proportion of missing values (affected_services, sector, contracted_service), imputation based on external sources was applied using a complementary customer database containing up-to-date information on location and subscribed services. For the remaining categorical variables with sporadic missing values, mode imputation was used. After the imputation and validation process, the dataset reached 0% missing values, resulting in a consolidated dataset ready for frequent pattern analysis.

III.4 DISTRIBUTION OF KEY VARIABLES

Distribution tests were conducted on variables relevant to incident analysis, including *incident_category*, *incident_type*, *root_cause*, *affected_technology*, *affected_services*. Table 2 presents the results corresponding to *categoria_incidente*.

Table 2: Variable analysis – “incident_category.”

incident_category	Frequency	Percentage (%)
service	22017	59.70
customer_service	9416	25.53
infrastructure	5445	14.76
chi2 = 12180.30, p = 0.0000 → The distribution is NOT uniform. (p < 0.05)		

Source: Authors, (2026).

The results indicate a significant concentration in the “serviço” category (59.70%), followed by “customer_service” (25.53%) and “infrastructure” (14.76%). The chi-square test ($\chi^2 = 12,180.30$, $p < 0.05$) confirms that the distribution is not uniform graphically illustrates this distribution.

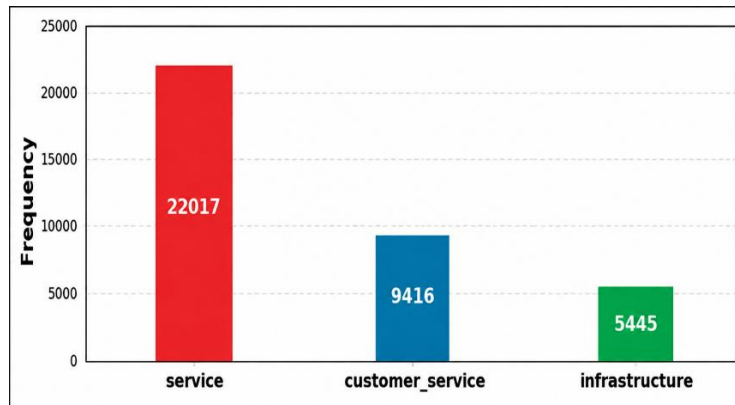


Figure 2: Distribution plot – “incident_category”.

Source: Authors, (2026).

In the case of Incident_Type (Table 3), the largest proportion corresponds to service degradation (48.2%), followed by equipment manipulation (18.09%) and service intermittency (11.5%). The percentages decrease substantially for categories such as electrical failure (1.61%) and DNS error (0.03%). The chi-square value $\chi^2 = 103,576.58$ ($p < 0.05$) further confirms the presence of a highly skewed distribution.

Table 3: Summary of the analysis of the variable “tipo_incidente”.

incident_type	Frequency	Percentage (%)
service_degradation	17775	48.2
equipment_tampering	6673	18.09
service_intermittency	4242	11.5
fiber_cut	3005	8.15
power_failure	595	1.61
dns_error	11	0.03
chi2 = 103576.58, p = 0.0000 → The distribution is NOT uniform. (p < 0.05)		

Source: Authors, (2026).

III.5 VARIABLE CORRELATION ANALYSIS

Association analysis using Cramér's V made it possible to identify significant relationships among categorical variables. Figure 3 presents the overall correlation matrix. Highly redundant associations were identified, such as “branch–city” and “affected_services–service_contracted”, with values close to 1. In these cases, the variables providing greater analytical context (“city” and “service_contracted”, respectively) were retained.

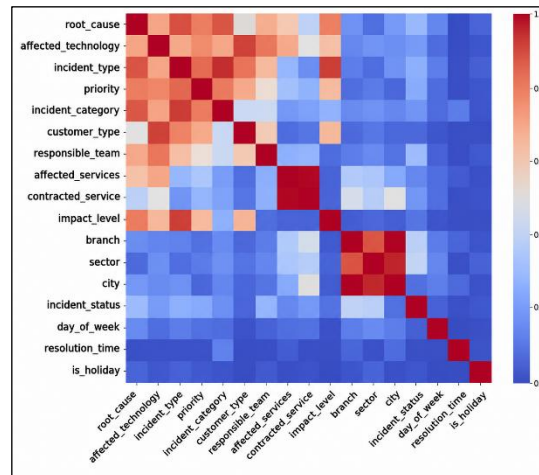


Figure 3: Variable correlation matrix; Cramér's V measure.
Source: Authors, (2026).

Other relevant associations include incident_type–root_cause (0.94), incident_category–incident_type (0.97), and affected_technology–customer_type (0.95), reflecting structural relationships among the nature of the incident, its underlying cause, and the customer profile. Figure 4, highlights the variables with the highest degree of association.

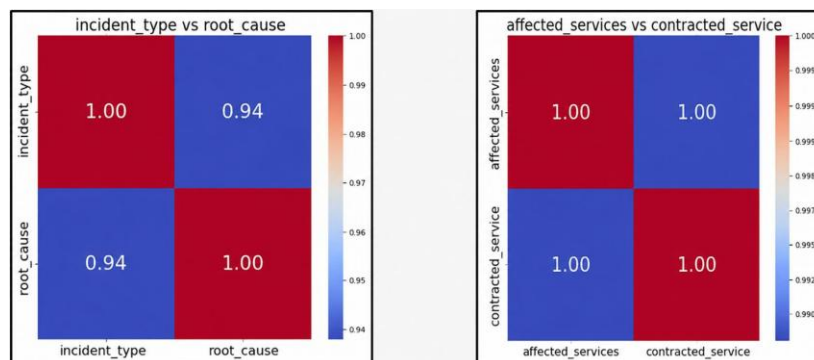


Figure 4: Variables With High Correlation Index.
Source: Authors, (2026).

Table 4 summarizes the most relevant associations with Cramér's V values greater than 0.3.

Table 4: Top 10 relevant associations (Cramér's $V \geq 0.3$).

Variable 1	Variable 2	Cramér's V
branch	city	0.999973
affected_services	contracted_service	0.995605
incident_category	incident_type	0.975532
city	sector	0.973270
incident_type	impact_level	0.961022
affected_technology	customer_type	0.948128
incident_type	root_cause	0.937842
incident_category	root_cause	0.926151
responsible_team	affected_technology	0.833765
incident_type	customer_type	0.818316

Source: Authors, (2026).

Among the highlighted associations are the variables “branch” and “city”, with a value close to 1, making them practically equivalent; the variable city was retained because it provides a more general analytical context. This is followed by “affected_services” and “contracted_service”, with a value of 0.9956. This analysis was applied to each association generated using Cramér's V .

III.6 SELECTION OF VARIABLES FOR PATTERN ANALYSIS

Based on redundancy reduction and the informative value of each attribute, eight variables were selected for frequent pattern analysis, as detailed in Table 5.

Table 5: Variables selected for frequent pattern analysis.

No	Variable	Reason
1	incident_type	Defines the main event.
2	priority	Reflects urgency / impact.
3	root_cause	Key to understanding the root cause.
4	affected_technology	Shows critical infrastructure.
5	impact_level	Degree of impact.
6	city	Provides granular location information.
7	affected_services	Shows the affected customer service.
8	incident_category	Shows the classification of events.

Source: Authors, (2026).

III.7 IDENTIFICATION OF FREQUENT PATTERNS

For frequent pattern analysis, the Apriori, FP-Growth, and ECLAT algorithms were applied using minimum thresholds of support = 0.1, confidence = 0.73, and lift = 0.8 [17]. The first two models generated highly consistent itemsets and association rules. **Erro! Fonte de referência não encontrada.** Table 7 summarizes the main frequent items identified by both models.

Table 6: Top 5 frequent itemsets – Apriori & FP-Growth model.

Support	itemsets
0.75915	city_quevedo
0.54162	end_user_equipment_affected_technology
0.48199	service_degradation_incident_type
0.41502	city_quevedo
0.40067	end_user_equipment_affected_technology

Source: Authors, (2026).

Among the most relevant patterns, “city_quevedo” stands out, appearing in more than 75% of the incidents, followed by end_user_equipment_affected_technology (≈54%) and “service_degradation_incident_type” (≈48%). Likewise, “root_cause_network_backbone_congestion” appears in approximately 33% of the records, indicating a recurring problem in the network infrastructure.

III.7.1 Dispersion Of A-Priori And FP-Growth Models

Figure 5 shows the *dispersion* of rules for both models, confirming the consistency of the obtained results despite differences in their processing mechanisms.

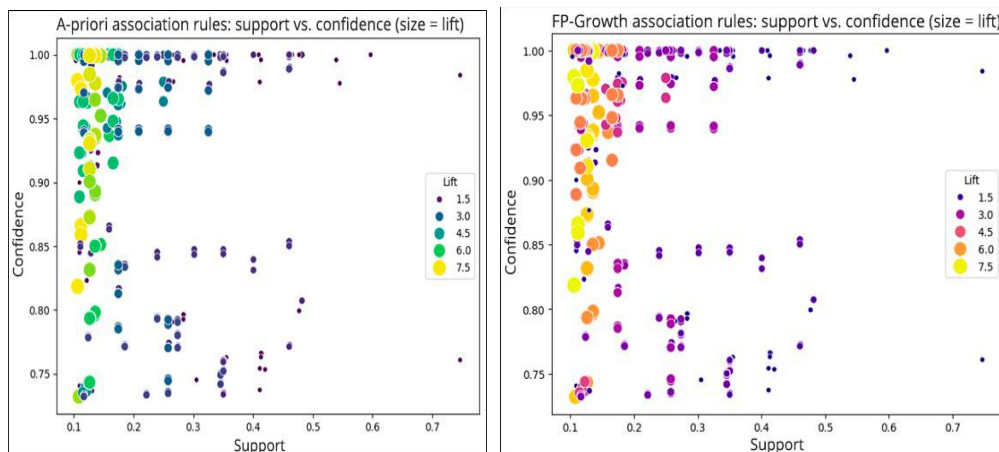


Figure 5: Dispersion of association rules (A-priori & FP-Growth).

Source: Authors, (2026).

Lift values between 1.5 and 7.5 indicate moderate to strong associations that, although infrequent due to their low support, result in reliable rules [15]. The main difference lies in data processing: while A-priori iteratively generates candidate itemsets, FP-Growth uses a compact structure (FP-Tree) to extract frequent itemsets [10], [16]. Nevertheless, the obtained results largely coincide, reaffirming the consistency and validity of the discovered patterns [18].

III.7.2 ECLAT Model

The analysis using the ECLAT model made it possible to visualize which combinations of attributes appear together most frequently. Unlike A-priori or FP-Growth, which tend to highlight complex and conditional relationships, ECLAT detects attributes that coexist with high frequency without emphasizing causality (see Table 7).

Table 7: Top 5 most frequent attributes; ECLAT Model.

Index	itemset	support
38	('individual_impact_level',)	0.9818
14	('is_holiday_no',)	0.9809
40	('residential_customer_type',)	0.9694
1006	('individual_impact_level', 'residential_customer_type')	0.9672
497	('is_holiday_no', 'individual_impact_level')	0.9631

Source: Authors, (2026).

The model highlights “individual_impact_level”, present in more than 98% of the records, suggesting that most incidents affect customers on an individual basis. This pattern, together with “residential_customer_type” and “is_holiday_no”, defines the predominant context in which incidents occur.

III.8 PATTERN-BASED REFERENCE FRAMEWORK ALIGNED WITH ITIL V4

The identified patterns were integrated into an operational reference framework aligned with ITIL v4 and adapted to the needs of the telecommunications company. The framework is structured into eight main components, following the Service Value System (SVS) approach and oriented toward the effective management of technological incidents (see figure 6).

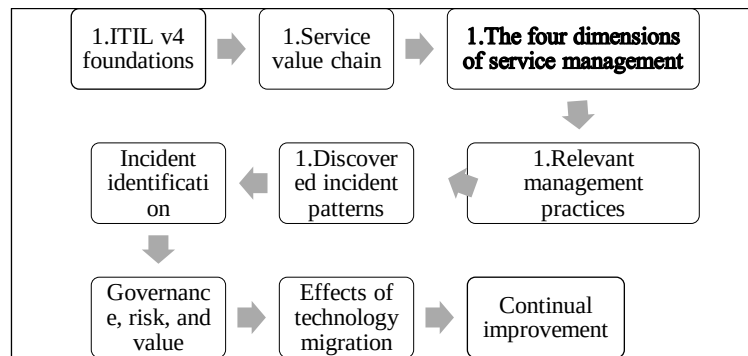


Figure 6: General architecture of the adapted reference framework.

Source: Authors, (2026).

The following operational alignment matrix presents a summary of the transition between the discovered patterns and the structure of the reference framework, demonstrating how each finding is translated into concrete actions within the components of ITIL v4 adapted to the needs of the telecommunications company (see Table 8).

Table 8: Operational alignment matrix (summary).

Framework component	Specific pattern (Data input)	Suggested operational use	Objective (ITIL v4)
Incident management practices	98.18% of incidents involve individual impact, and 96.94% correspond to residential customers.	Automate categorization and assign fast-resolution workflows for end users.	Efficiency in service restoration.
Risk governance	75.9% of total incidents are concentrated in the city of Quevedo.	Implement localized technical audits and contingency plans for this critical area.	Mitigation of structural weaknesses.
Continual improvement	A 93% confidence association between damaged connectors, CATV equipment, and service degradation.	Revise physical installation standards and improve the quality of customer-end equipment materials.	Prevention of recurrent incidents.
Infrastructure planning	Core network congestion appears as the root cause in 33% of the records.	Prioritize bandwidth expansion investments in the identified saturated nodes.	Ensure service capacity and availability.
Value chain	Service degradation is the predominant incident type (48.2%).	Adjust service level agreements (SLAs) to prioritize slow service over low-frequency total outages.	Maximize customer satisfaction.

Source: Authors, (2026).

IV. CONCLUSIONS

This study analyzed real technological incidents reported by a telecommunications company in Ecuador, applying data science techniques to identify frequent patterns with operational impact. Dataset preprocessing, together with association analysis using Cramér's V, enabled the reduction of problem dimensionality and the selection of eight key variables representative of the dynamics of technological incidents and suitable for pattern mining. The results reveal a significant concentration of incidents in the city of Quevedo, mainly associated with service degradation and failures in customer-end equipment. Recurrent root causes include core network congestion, power outages, and fiber cuts, predominantly affecting residential customers with basic services. Although most incidents are individual and are resolved successfully, their high frequency exposes structural weaknesses in the infrastructure and technical support processes, justifying the need for data-driven preventive actions. As its main contribution, this work translates frequent incident patterns into an operational reference framework aligned with ITIL v4, integrating empirical findings within a service management approach oriented to the Service Value System. The proposed framework articulates key components such as incident management practices, the service value chain, risk governance, and continuous improvement, enabling the adaptation of ITIL guidelines to the company's real operating conditions. From a practical perspective, the framework supports evidence-based decision-making, contributing to reduced response times, prioritization of recurrent incidents, and improved customer satisfaction. From an academic standpoint, the study provides a replicable approach for analyzing technological incidents in telecommunications organizations by combining data mining techniques with service management best practices. As future work, the analysis could be extended by incorporating predictive learning techniques to anticipate incidents, as well as by evaluating the impact of the proposed framework through performance indicators measured before and after its implementation.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Angel Ivan Torres Quijije, Anthony Jahir López Coello, Diego Fernando Intriago Rodriguez and Emilio Rodrigo Zhuma Mera.

Methodology: Angel Ivan Torres Quijije and Anthony Jahir López Coello.

Investigation: Angel Ivan Torres Quijije and Anthony Jahir López Coello.

Discussion of results: Angel Ivan Torres Quijije, Anthony Jahir López Coello, and Diego Fernando Intriago Rodriguez.

Writing – Original Draft: Anthony Jahir López Coello.

Writing – Review and Editing: Angel Ivan Torres Quijije and Anthony Jahir López Coello.

Resources: Anthony Jahir López Coello.

Supervision: Angel Ivan Torres Quijije and Emilio Rodrigo Zhuma Mera.

Approval of the final text: Angel Ivan Torres Quijije, Diego Fernando Intriago Rodriguez. and Emilio Rodrigo Zhuma Mera.

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