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Data Mining to Assess Organizational Transparency across Technology Processes: An Approach from IT Governance and Knowledge Management

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Abstract: Information quality and organizational transparency are relevant issues for corporate governance and sustainability of companies, as they contribute to reducing information asymmetry, decreasing risks, and improving the conduct of decision-makers, ensuring an ethical standard of organizational control. This work uses the COBIT framework of IT governance, knowledge management, and machine learning techniques to evaluate organizational transparency considering the maturity levels of technology processes applied in 285 companies of southern Brazil. Data mining techniques have been methodologically applied to analyze the 37 processes in four different domains: Planning and organization, acquisition and implementation, delivery and support, and monitoring. Four learning techniques for knowledge discovery have been used to build a computational model that allowed us to evaluate the organizational transparency level. The results evidence the importance of IT performance monitoring and assessment, and internal control processes in enabling organizations to improve their levels of transparency. These processes depend directly on the establishment of IT strategic plans and quality management, as well as IT risk and project management, therefore an improvement in the maturity of these processes implies an increase in the levels of organizational transparency and their reputational, financial, and accountability impact.

Keywords: organizational transparency; information quality; information asymmetry; IT governance; technology processes; COBIT; monitoring; internal control

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1. Introduction

Competitive companies are those that, in addition to being efficient and effective in their practices, are also transparent [1,2]. Transparency is a concept that directly depends on high-quality information and services [3]. At present, companies have all their practices supported by systems, and it is in their performance that it is possible to assess the level of transparency and reduction of asymmetry [4], mainly to determine, in detail, their financial situation [5] and consequently ensure better governance and sustainability.

Organizational transparency is a key factor in generating trust, which is achieved when the company responds to demands for information on its management. Transparency also opens the possibility that a company's real information can be consulted by the different stakeholders affected by it, so that they can take decisions in full knowledge of the facts and without information asymmetry. Organizational transparency is related to the quality of information, in that it must be truthful, relevant, understandable, useful, verifiable, and easily accessible, it must be provided voluntarily, and go beyond what is required by regulation. For companies to achieve an adequate level of organizational transparency, they need to strengthen the governance of IT and knowledge management processes, as well as develop an effective communication policy. The quality of information and services significantly depends on technology processes with a high maturity level integrated into technology governance that improves different managers' behaviors. Therefore, the quality of information and its appropriate dissemination ensure adequate transparency. That is why constantly evaluating the technology processes that manage information and knowledge becomes practically an obligation for benchmark companies in the market, creating an ethical and profitable standard from the organizational control perspective. In this sense, high maturity levels in processes (e.g., assessing and managing risks) lead to low vulnerability and enable efficient control and good corporate governance practices. Referring to the ethical standard, it can also be affirmed that when the technological processes that sustain the company's systems are well controlled, a high-performance organizational culture is maintained, which reduces the possibilities of fraud [6,7] and can improve the level of labor motivation.

The assessment of technology processes depends on how such processes are structured, designed, outsourced, and/or developed, and on the maturity level they present while performing their activities. To this purpose, different frameworks operate at this level of technology processes such as the ISO 27004 of information security management [8], the ISO 31000 of risk management, and the best practices in Information Technology service management like ITIL, the COBIT family, and the ISO 38500 of IT Governance [9]. These frameworks set up strong Information Technology Governance (ITG), which ensures the alignment of IT with business strategies, organizational processes compliance, better accountability, and improves the companies' transparency, through more desirable behaviors in the use of technology. The direct consequence is the increase in the company's competitiveness in an increasingly unstable and complex market.

The COBIT framework—Control Objectives for Information and Related Technologies—helps organizations to develop, implement, monitor, and improve IT governance and information management [10], and is used in this work considering 4 domains and 34 processes that are analyzed in 285 companies. The four COBIT domains are Planning and Organization (PO), Acquisition and Implementation (AI), Delivery and Support (DS), and Monitoring (MO).

Therefore, this work developed the following research question: What is the level of transparency of companies according to the maturity of technological processes? This research question is addressed through the Data Mining (DM) technique that analyzes the maturity levels in a database of COBIT processes and is relevant because it allows companies to improve the quality of the information in a practical way through better IT governance, and in a theoretical way by understanding how machine learning and data mining techniques can help to know the state of their organizational processes and decide the company's investments in improving them.

The related aim was to assess organizational transparency and its relationship with technological processes in a sustainable corporate governance framework. The research objective seeks to establish better relationships between technology process performance and organizational transparency, conceptually and practically, developing the use of robust data mining techniques to predict future investments (showing where technology maturity is lower and thus knowing where to devote more effort and resources), enable technology risk mitigation, better manage internal projects, link better IT governance with accountability, and finally, better understand how to conduct technology governance to achieve a higher level of adequacy for sustainability, reputation, and accountability to society.

In this research, different specialists have assessed the technology processes considering their maturity levels to determine the organizational transparency attributed to them. Four learning techniques—Inductive Learning for building decision trees, Naive Bayes, Multi-layer perceptron, and the Lazy learning method—were used to build a computational model with a decision tree approach, which enabled the analysis of their relationship with levels of organizational transparency.

The application of data mining [11] and machine learning techniques [12–14], with a specific application in Knowledge Discovery from Databases (KDD) algorithms, makes it possible to find real relationships and dependencies between processes and discover knowledge to improve organizational transparency. This contributes to the sustainability of companies that can focus their investments on the technological and corporate governance processes (internal controls, compliance, systems outsourcing, quality management, automation, risk control, information security, etc.) that have the greatest impact on the stakeholders and the market.

2. Literature Review

For the literature review, topics related to organizational transparency and assessment of technology processes were considered with COBIT and Data Mining.

2.1. Organizational Transparency

The transparency of organizations depends on information dissemination quality, including intensity, measuring principles, opportunity, and credibility. In other words, the higher the information quality, the lower the information asymmetry. It also includes the delivery of information to the public that it wants to reach, as well as the use that the public makes of organizational information, considering the relation of the existing social contract [15,16].

For that reason, organizational transparency in the 21st-century economy is aligned with governance, Knowledge Management (KM), and organizational performance. It enhances knowledge generation by improving the flow of knowledge, which promotes the firm's performance [17]. Knowledge-based organizations seek efficient management approaches and sustainable development practices to perform efficiently in the dynamic business environment. Therefore, knowledge management practices—organizational transparency, information dissemination quality, and information asymmetry reduction—are significant factors in achieving sustainable organizational performance in dynamic and changing environments [4].

KM has important implications when applied to the concept of sustainability and it has been recommended to prioritize research on KM and sustainability [18], including organizational transparency regarding corporate socio-environmental and financial reporting, in developing societies. In today's business context, corporate governance and financial transparency influence the performance of companies [2]. This approach provides an understanding of the importance of enhancing the accessibility and transparency of relevant and reliable information about the financial and non-financial aspects of an entity.

Organizational transparency involves, among other factors, the desire to reduce the information asymmetry that is established between an organization and the interested parties [1]. It means informing different stakeholders about organizational actions and activities by proving they meet the previously contracted expectations and by reducing agency conflicts [19] through technology corporate governance [20], which relates responsibilities and behavior to the appropriate use of technology in the company.

Organizations should report and explain the impacts of their policies, decisions, actions, products, and performance by informing all business partners about the process and the result of the organizational activities. Therefore, information asymmetry is a premise of contractual relationships that makes the completeness of contracts impossible [21–23]. The information level is not the same for all parties in a contract and, consequently, perfect control from one party over the other one is not possible due to information asymmetry [21,23]. This asymmetry leads to opportunistic behaviors that create more pressure for transparency, showing that investors and stakeholders want more information [22] to continue investing in organizations and ensure their continuity [24]. Thus, information asymmetry, which creates stakeholder pressure, is an argument for organizational transparency [25,26].

Information asymmetry is associated with incomplete and imperfect information, producing distortions in the knowledge managed by different actors, which generates costs for corporate performance and jeopardizes the sustainability of the organization. In addition, it is affected by the actions of organizations when they manage information disclosure, with the intention of withholding, delaying, or not being transparent [21,22,27]. Therefore, there is a relationship between transparency and the decrease in information asymmetry [24,26,28].

The disclosure also effectively contributes when it levels the parties to a contract, thus reducing information asymmetry [22,24,29] and consequently increasing transparency. Therefore, information disclosure serves as a strategy to reduce problems and costs arising from information asymmetry [24,27,30]. Besides, the principle of transparency guides organizations regarding information disclosure [1].

The governance structure should ensure the dissemination of financial and non-financial information through channels that provide for equal, timely, and cost-efficient access to all the relevant organizational information [1]. It is important to highlight the need to acquire financial information in time due to its importance for the pricing of organizations [27]. Financial and non-financial information transparency is one of the key factors for stakeholder's trust in an organization [31].

In addition, organizations should ensure information dissemination through channels that provide equal, timely, and cost-efficient access to all the relevant organizational issues [1]. On the one hand, organizational transparency depends on dissemination quality. On the other hand, it depends on the information transmission to the stakeholders that it intends to reach, as well as on the use of organizational information by the public [15,16].

Figure 1 shows that organizational transparency has gaps caused by information asymmetry.

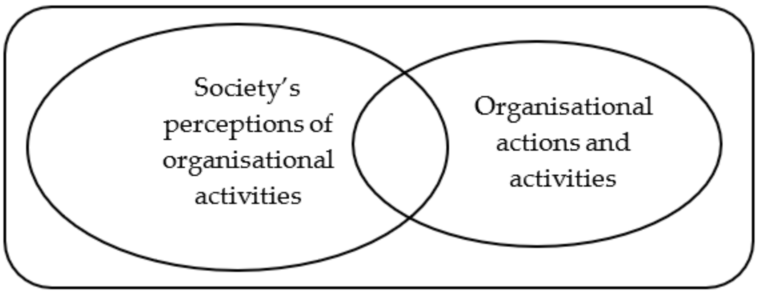

Figure 1. Gaps in organizational transparency. Adapted from [32].

The overlap area of the circles represents the congruence between the organizations' activities and the stakeholders' perceptions of those actions. The aim of organizations should be to ensure the overlap area of the circles is as broad as possible to reduce the gap caused by information asymmetry in the communication between organizations and the society in which they operate [32,33].

The concept of transparency has been promoted in business literature as an ethical and advantageous requirement [34,35]. However, there are also dysfunctions associated with transparency as an organizational control mechanism, such as the risk that individuals focus only on what is made transparent [36]. Whilst some managers may be reticent to share the results in relation to the development of their activity, the numbers, or the behavior of their company, transparency can be a great ally in the strategy of a company. Organizations can find strategies to improve trust and reinforce their reputation (one of the main business assets) by enhancing transparency, since it is an ethical standard that improves the company's image. Transparency is therefore identified as a factor for improving business competitiveness.

Information, when not well managed with appropriate disclosure, can compromise organizational continuity by revealing strategic content that, in turn, jeopardizes the company itself [24,27,36,37]. In addition, there is a gap between optimal transparency and satisfactory transparency. Organizations aim to achieve optimal transparency, but that transparency may not be satisfactory for stakeholders [38]. Therefore, transparency has value. and the paradox when involving it in organizations is evident [36,39], which makes some control and structure mechanisms over information technology necessary. Such mechanisms meet the strategic management demands.

2.2. Assessment of Technology Processes with COBIT

Companies are structured by information systems, and transparency means well-dimensioned and well-structured technology processes in an IT Governance context [20], where the COBIT framework is positioned and operates to make stronger applications [10,40].

IT Governance promotes the implementation of internal and external controls by means of mechanisms and principles that aim to minimize conflicts of interest among agents, managers, and the main owners or shareholders. Thus, it increases organizational transparency, reducing risks and information asymmetry [10,41–46].

This transparency provided by technology processes also enables legal compliance [47,48] and better accountability when conducting an ITG audit. This was the case in [49] and in the audit study of the accounting information system using COBIT, which focuses on the Deliver and Support (DS) domain [50].

Previous authors [20,51] have defined that, in the ITG context, decision and responsibility matrix rights exist to motivate wanted behaviors in technology use. Regarding organizational transparency, it is possible that the ITG, with greater control over the company's activities, implements related processes, structures, and mechanisms [52], thus allowing technology and employees to perform their tasks with responsibilities supporting the previously defined strategies and to create value for the company, always seeking to increase competitiveness.

Another study [53] adopted IT Governance in the banking and insurance sector through a 5-year longitudinal study in which they identified an increase in maturity levels in the observed companies, as well as in social media applications, as was the case in the study by [54] in their analytical review based on COBIT.

The search for a better adaptation to transparency requirements and its derivatives [55] (IBGC, 2014) through technology governance [10] enhances the company's sustainability, thus reducing the separation from the technology area due to intensive use of frameworks such as COBIT [56]. Such frameworks integrate IT objectives and information, processes, and structure enablers, among other aspects (COBIT 5 Goals Cascade). This is done by involving the assessment of technology processes and risks [57] through the analysis of their maturity levels [58] in CRM [59], but above all, by creating value supported by the pillars of benefits, risks, and resources [10].

The COBIT framework is presented in their manageable levels to treat IT processes in 4 domains and 34 processes with the most varied applications, as observed while mapping the COBIT domains for communication and control in outsourced projects of information systems [60]. This is the scope developed by this study, which focused on a model based on DM.

According to [61], the four (4) COBIT domains are Planning and Organization (PO), Acquisition and Implementation (AI), Delivery and Support (DS), and Monitoring (MO), which are briefly described below [20].

Planning and Organization (PO): It covers, through 10 processes, strategies, and tactics with the aim of identifying the best way for IT to collaborate in the accomplishment of business purposes, highlighting planning, communication and IT, and business strategic management. It also seeks to implement the technological infrastructure.

Acquisition and Implementation (AI): By means of seven processes, it handles what needs to be identified, developed, acquired, implemented, and integrated into the business process. Besides, alterations and maintenance of the existing systems are covered by this domain to ensure that solutions keep accomplishing the business' purposes.

Delivery and Support (DS): It involves the delivery of required services. It includes service delivery, security and continuity management, service support for users, and data and operational resources management. It consists of 13 processes.

Monitoring (MO): It is related to the regular assessment of processes to ensure quality and adherence to control requirements. This domain consists of four processes addressing performance management, internal control monitoring, regulatory adherence, and governance.

COBIT domains and processes are integrated so that IT succeeds in satisfying business requirements. The business orientation that COBIT focuses on is to align business goals with IT goals, providing metrics and maturity models to measure their achievement. Thus, PO provides direction for solution delivery (SD) and service delivery (SD). AI provides the solutions and passes them on to turn into services. DS receives the solutions and makes them usable by the end users, and MO monitors all processes to ensure that the intended direction is followed.

The need for IT governance to improve enterprise performance, focusing on assessing the maturity level of IT processes related to Delivery and Support (DS) and Monitoring (MO), should be emphasized [52]. In addition, previous research [62] points out that internal control contributes to corporate sustainability, ensuring improvements in efficiency and effectiveness in operations, reliable reports, and compliance with applicable laws and regulations, having a positive effect on Environmental, Social, and Governance ratings.

The COBIT framework supports IT governance by providing a methodology to ensures that the IT area is aligned with the companies' purposes, enabling business, and maximizing benefits. The IT resources are responsibly used, and IT risks are appropriately managed. Thus, focus areas related to Strategic Alignment, Delivery of Value, Risk Management, Resources Management, and Performance Measurement are described, according to the executive summary [20]. The database studied is related to these domains and their respective processes, assessing a consolidated maturity level [63], which was assessed in this work for multiple frameworks (ITIL, COBIT, CMMI-SCV).

For this work, COBIT was used [20] because it is the result of research developed over some years with maturity level applications in a synthetic manner in 285 companies located in the southern region of Brazil as well as in some companies outside this region.

3. Materials and Methods

The method used in the computational model that assessed companies' transparency for COBIT-based technology processes was based on Design Science Research (DSR) [63–65]. DM was applied as an analytical decision-making technique and operated with Weka [66] as an open-source computational tool.

Data mining is closely related to knowledge management, which, according to previous research [67], is strongly correlated with innovation capability. DM enables identifying patterns, predicting situations [68], discovering implicit knowledge in databases, and performing machine learning, among other resources of equal robustness. This is done by combining statistical techniques, artificial intelligence, and highly commonly applied business rules in the financial, healthcare, and sales sectors [69]. It is also applied to analyze the customer value in B2B networking, as well as in different audits, including the assessment of service levels generated [70] and even increasing guarantees of demeanor in online business [71].

Therefore, this type of modelling allows for greater accountability in the company, greater compliance, lower risks, less information asymmetry, but, above all, greater organizational transparency in diverse business applications and even in e-commerce, which is currently widespread with the automated acquisition of airline tickets and hotel bookings all over the world.

These approaches need to integrate data in a very efficient way as analyzed in [72], such as the relations of DM x Business Intelligence [73] x Data Warehouse, even achieving machine learning and knowledge generation [74] that connect social networks [75].

According to [76], Data Mining is a term used to describe the automatic discovery of organizations in databases. Data mining algorithms can be divided into 4 consolidated categories: *Classification* (supervised induction to predict), *clustering* (divides a database into segments whose members share similar qualities in clusters), *association* (relations between items that are together in a record), and *sequence discovery* (identification of associations over time with regressions and forecasting).

Therefore, information transparency is dependent on different aspects that characterize reliable information, which complies with external and internal laws and regulations, thus providing greater transparency and a better business strategy [77].

Consequently, this type of approach needed a better DM technique solution since it is a business decision, as observed in [11]. Then, COBIT [20] was used in these analyses, thus describing the aspects or variables grouped in the domains PO, AI, DS, and MO, as previously presented.

Each of these aspects is assessed according to six maturity levels:

0—*Non-existent*: At this level, there is an absolute lack of process. The organization is not aware of the consequences that the lack of process can involve.

1—*Initial*: At this level, processes are sporadic and disorganized. There is no documentation and no control at all.

2—*Repeatable but intuitive*: At this level, processes follow a pattern of regularity and are dependent on individuals' knowledge.

3—*Defined*: At this level, processes are established and accomplished. This level marks the beginning of the use of control indicators.

4—*Managed*: At this level, processes are integrated and aligned. Goals and plans are based on consistent data and indicators.

5—*Optimized*: Good practices are followed and automated, based on continuous improvement results.

Data Mining is a technique of data analysis, knowledge generation, and machine learning that is well configured in the context of Design Science Research (DSR) and has presented a lot of robustness in the treatment of these technology process data. Therefore, the application that was carried out is presented below. Thus, from these variables that measure the maturity level in 34 organization processes, it has been possible to evaluate the organization's transparency level and its consequent asymmetry reduction. To this end, three levels have been established: High, Medium, and Low, applied to the consolidated maturity levels of COBIT in terms of the assessment of organizational transparency.

The analyses were carried out on a database of 285 companies, with the assessment of the transparency level of technology processes made by 548 managers and technicians, from medium-sized and large companies in various sectors of economic activity, prioritizing the industrial sectors of chemical, automotive, and metallurgy companies, as well as the financial services and commerce sectors.

4. Results and Discussion

Techniques for knowledge discovery from an inductive learning approach and the results found regarding the level of organizational transparency associated with the maturity of technological processes are presented in this section.

Data Mining in COBIT to Assess Transparency

The study was carried out on the basis of responses from specialists who evaluated each process and attributed a level of transparency considering its maturity level. These case studies have helped to build a computational model that automates the process of calculating the transparency level of technology processes for an organization considering their maturity level. In other words, an F model has been built to calculate the Transparency Level (Tl) of an Organization (O) by considering its technology processes in terms of the maturity approach:

$$TL(O) = F(PO1, \ldots, PO10, AI1, \ldots, AI7, DS1, \ldots, DS13, MO1, \ldots, MO4)$$

Knowledge discovery techniques have been used to build the F model. These techniques allow data analysis to be carried out, and they are known as Machine Learning and Data Mining techniques [14,78].

Knowledge discovery is the non-trivial extraction of implicit information, previously unknown and potentially useful, from a collection of data. One of the learning methods is Inductive Learning, which is used to gain knowledge (formulated as intentional descriptions) from different examples. Another learning method is Lazy Learning, in which generalization beyond the training data is delayed until a query is made to the system.

It is formally said that an example is a pair (X, f(X)), where X is the input vector and f(X) is the function output that was applied to X. The goal of inductive inference—Inductive Learning—is to give a set of examples f, producing a function h that approximates f. The function h can be expressed as a set of casual rules, an artificial neural network, a decision tree, etc. In the case of Lazy Learning, the same solution is obtained, and it offers the most similar case to the problem that it is required to infer. In other words, given the organization O described by the vector X that identifies its different aspects, X = (PO1, . . . , PO10, AI1, . . . , AI7, DS1, . . . , DS13, MO1, . . . , MO4), it returns the transparency level of the most similar case to O.

In this work, four learning techniques were used to build a computational model to calculate the level of transparency of an organization based on the assessment of the maturity level of its indicators for technological processes. Such techniques, according to [79,80], are the following:

1—The Inductive Learning methods, decision tree building approach (J48).

2—Naive Bayes.

3—Multi-layer perceptron (MLP).

4—Lazy Learning k-NN (IBK).

The quality assessment of the built model has been carried out by using knowledge discovery quality measures [81].

The inference results appear in Table 1 and correspond to the % of correct classifications in accordance with different controls or test samples and take the default parameters for the different learning methods used.

Table 1. Transparency level classification according to correct classifications percentage.

	With the Entire Training Set	With 34% of the Training Set	With 5 folds Cross Validation
Naive Bayes	85.5%	85.5%	84.3%
J48	96.7%	84.4%	78.4%
IBK K = 1	99.6%	76.9%	78.2%
MLP	99.5%	83.3%	80.2%

On the one hand, an example of the resulting outputs when applied in Weka J48 to the entire training set is shown in Figure 2. The results are specified by category. On the other hand, Figure 3 shows the decision tree with a 0.9 confidence factor.

```
 == Summary ===
Correctly Classified Instances         529               96.7093 %
Incorrectly Classified Instances        18                3.2907 %
Kappa statistic                          0.9489
Mean absolute error                      0.0401
Root mean squared error                  0.1397
Relative absolute error                  9.3502 %
Root relative squared error             30.1643 %
Total Number of Instances              548

=== Detailed Accuracy By Class ===
TP Rate   FP Rate   Precision   Recall  F-Measure   Matthews CC  ROC Area  Class
  0.972     0.012      0.981     0.972    0.976       0.961      0.995    LOW
  0.955     0.025      0.963     0.955    0.959       0.932      0.985    MEDIUM
  0.982     0.014      0.949     0.982    0.966       0.956      0.995    HIGH
=== Confusion Matrix ===
   a   b   c   <-- classified as
 206   6   0 |   a = LOW
   4 211   6 |   b = MEDIUM
   0   2 112 |   c = HIGH
```

Figure 2. Results of applying J48.

```
J48 pruned tree
------------------
MO1 - Monitors and assesses IT performance.  <= 3
|   MO2 - Monitors and assesses internal control. <= 1
|   |   PO5 - Manages the IT investment. <= 3
|   |   |   PO8 - Manages the quality. <= 3: LOW (127.41/1.0)
|   |   |   PO8 - Manages the quality. > 3
|   |   |   |   PO1 - Defines the IT strategic plan. <= 2: LOW (7.0)
|   |   |   |   PO1 - Defines the IT strategic plan. > 2: MEDIUM (2.0)
|   |   PO5 - Manages the IT investment. > 3
|   |   |   PO4 - Defines the IT organization and its relations.  <= 2: LOW (6.0)
|   |   |   PO4 - Defines the IT organization and its relations. > 2
|   |   |   |   DS6 - Identifies and allocates costs <= 2: LOW (2.0)
|   |   |   |   DS6 - Identifies and allocates costs > 2: MEDIUM (10.0/1.0)
|   MO2 - Monitors and assesses internal control. > 1
|   |   DS10 - Manages the problems. <= 1
|   |   |   PO9 - Assesses and manages the risks. <= 2
|   |   |   |   PO10 - Manages the projects. <= 3: LOW (36.15/1.0)
|   |   |   |   PO10 - Manages the projects. > 3: MEDIUM (2.0)
|   |   |   PO9 - Assesses and manages the risks. > 2
|   |   |   |   PO5 - Manages the IT investment. <= 1: LOW (3.0)
|   |   |   |   PO5 - Manages the IT investment. > 1
|   |   |   |   |   AI6 - Manages changes <= 1: LOW (2.0)
|   |   |   |   |   AI6 - Manages changes > 1: MEDIUM (13.0/1.0)

Number of Leaves:     47
Size of the tree:     93
```

Figure 3. Decision tree resulting from applying J48.

The results of applying J48 by using the entire training set show that 96% of the examples in the sample are correctly classified. On the other hand, only 18 examples, 3.39% of the examples, were incorrectly classified. The category in which best results are achieved according to *TP-Rate* = *TP/P* is the High category with 0.98 and the best *Precision* = *TP/(TP + FP)* is LOW, see in [82] other measures of the assessment developed.

Figure 3 presents the entire decision tree created. The attribute MO1 (Monitors and assesses IT performance), which is the most relevant one for the classification, is found at the tree's root. Then, MO2 (Monitors and assesses internal control), PO5 (Manages the IT investment), etc., appear in order of importance. The colon ":" presents the conclusion's definitions; in other words, it indicates what transparency level classification is reached: Low, Medium, or High. The numbers in parentheses represent the average number of examples in which that conclusion is correctly reached and also refer to the average number of wrong examples. If no number appears for the latter value, no wrong example exists.

For instance, in Figure 4, we only have the first decision tree fragment comprising three rules, which can be represented in natural language as:

```
MO1 - Monitors and assesses IT performance. <= 3
|   MO2 - Monitors and assesses internal control. <= 1
|   |   PO5 - Manages the IT investment. <= 3
|   |   |   PO8 - Manages the quality. <= 3: LOW (127.41/1.0)
|   |   |   PO8 - Manages the quality. > 3
|   |   |   |   PO1 - Defines the IT strategic plan. <= 2: LOW (7.0)
|   |   |   |   PO1 - Defines the IT strategic plan. > 2: MEDIUM (2.0)
```

Figure 4. First decision tree fragment.

Rule 1: If MO1 ≤ 3 and MO2 ≤ 1 and PO5 ≤ 3 and PO8 ≤ 3, then the transparency level is Low.

The level of transparency is Low (consequently, the asymmetry is high and the vulnerability to risks is high) when the technological process of monitoring and assessment of IT performance has a low maturity level, and jointly, the monitoring and evaluation of internal controls is initial or non-existent, with an IT investment management and quality management that is dependent on individuals' knowledge or is defined but at an early stage. With this information, greater investment in internal controls may be considered (i.e., paying attention to the COSO's Internal Control–Integrated Framework) and establishing quality controls (i.e., using a Kaizen system or even by improving a Plan–Do–Check–Act (PDCA) cycle).

Rule 2: If MO1 $\leq$ 3 and MO2 $\leq$ 1 and PO5 $\leq$ 3 and PO8 > 3 and PO1 $\leq$ 2, then the transparency level is Low.

This second result shows the need for the organization to develop a strategic IT plan, since otherwise, under the previous assumptions of IT performance maturity level being lower and the monitoring and evaluation of internal controls being initial or non-existent, transparency will be low even managing IT investments.

Rule 3: If MO1 $\leq$ 3 and MO2 $\leq$ 1 and PO5 $\leq$ 3 and PO8 > 3 and PO1 > 2, then the transparency level is Medium.

This third result points to the fact that the decision-maker will be able to raise the level of organizational transparency to the point of managing it, aligned with the organization's objectives, or even optimize it, investing in the establishment and development of IT strategic planning, improving the criteria for defining these plans through SWOT analysis, risk analysis, and rigorous monitoring of the indicators for the different IT strategic actions.

Rules 1–3 were determined from the decision tree generated with the entire dataset, considering the answers of 548 specialists who evaluated the companies' transparency levels attributed to their technological processes.

The inference results in Table 2 correspond to the absolute average error according to different control or test samples and again taking the default parameters.

Table 2. Transparency level classification according to absolute average error.

	With the Entire Training Set	With 34% of the Training Set	With 5-Folds Cross Validation
Naive Bayes	0.09	0.09	0.10
J48	0.04	0.13	0.15
IBK K = 1	0.004	0.15	0.14
MLP	0.01	0.11	0.13

The results of transparency level classification according to the absolute average error allow us to see the difference between the results that are achieved with the entire training sample and other partitions of them. IBK with K equal to 1 is more sensitive to the control sample. Overall, the absolute error oscillates between 0.10 and 0.15 with better results being observed by Naive Bayes and MLP and, therefore, where better generalization levels in learning are achieved.

All the results after applying Naives Bayes using 5-fold cross-validation as a sample appear in Figure 5 where, in addition, the results by category and the matrix to describe the performance of a classification model ("classifier") are specified. On the other hand, Figure 6 shows the results of applying an MLP with 34% of the training set as a control sample.

```
=== Run information ===
Scheme:       weka.classifiers.bayes.NaiveBayes
Relation:     cobitnuevo500-weka.filters.unsupervised.attribute.Remove-R1,3
Instances:    548
Attributes:   36

Test mode:    5-fold cross-validation
=== Summary ===
Correctly Classified Instances         461               84.2779 %
Incorrectly Classified Instances        86               15.7221 %
Kappa statistic                          0.7576
Mean absolute error                      0.1056
Root mean squared error                  0.3133
Relative absolute error                 24.6343 %
Root relative squared error             67.6689 %
Total Number of Instances              548

=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   Matthews CC  ROC Area  Class
  0.868     0.06       0.902     0.868    0.885       0.814      0.973    LOW
  0.787     0.12       0.817     0.787    0.802       0.672      0.922    MEDIUM
  0.904     0.062      0.792     0.904    0.844       0.803      0.982    HIGH

=== Confusion Matrix ===

   a   b   c   <-- classified as
 184  28   0 |   a = LOW
  20 174  27 |   b = MEDIUM
   0  11 103 |   c = HIGH
```

Figure 5. Naive Bayes results.

```
=== Run information ===
Scheme:       weka.classifiers.functions.MultilayerPerceptron -L 0.2 -M 0.2 -N 500 -V 0 -S 0 -
E 20 -H a
Relation:     cobitnuevo500-weka.filters.unsupervised.attribute.Remove-R1,3
Instances:    548
Attributes:   36

Test mode:    split 66% train, remainder test

=== Summary ===
Correctly Classified Instances         155               83.3333 %
Incorrectly Classified Instances        31               16.6667 %
Kappa statistic                          0.7447
Mean absolute error                      0.1193
Root mean squared error                  0.3163
Relative absolute error                 27.7611 %
Root relative squared error             68.0707 %
Total Number of Instances              186

=== Detailed Accuracy By Class ===
TP Rate   FP Rate   Precision   Recall  F-Measure   Matthews CC  ROC Area  Class
  0.928     0.12       0.821     0.928    0.871       0.791      0.966    LOW
  0.711     0.082      0.857     0.711    0.777       0.653      0.892    MEDIUM
  0.902     0.055      0.822     0.902    0.86        0.82       0.971    HIGH

=== Confusion Matrix ===

  a  b  c   <-- classified as
 64  5  0 |  a = LOW
 14 54  8 |  b = MEDIUM
  0  4 37 |  c = HIGH
```

Figure 6. Results of applying MLP to 34% of the set.

On applying Naives Bayes to the five partitions, 84.27% of the correct classifications are reached, on average, with an absolute error of 0.10. Again, the best *TP rate* category is High, and the best *Precision* category is Low. The Naive Bayes results for different partitions are very similar. The lowest indicator category is Medium.

When applying MLP when only 34% of the training sample examples are used, the results are 83.3% correct classifications and an absolute error of 0.1, very similar to those achieved with 5-fold cross-validation. The best *TP rate* category is Low, and the *Precision* behavior is similar for the different categories. The Medium category shows lower indicators.

Subsequently, we analyzed the IBK and MLP methods that are affected by parameters in learning, and they turned out to be those with the best average results according to the previous study. In the IBK case, an improvement is made by varying the K parameter. The applied distance functions do not change the results. Table 3 shows the results for K with values of 3 and 5. For higher K values, the result worsens.

Table 3. Better IBK results when varying K.

	With the Entire Training Set	With 34% of the Training Set	With 5-Folds Cross Validation
IBK K = 3	87.9% and 0.10	81.2% and 0.14	81% and 0.15
IBK K = 5	84.8% and 0.12	81.7% and 0.15	81.7% and 0.15

When working with partitions of the training set, IBK improves its results if the K parameter is modified, with similar results for K equal to 3, 4, or 5. For higher K values, worse results are achieved.

Figure 7 shows the results achieved with IBK for K = 3 for five partitions of the training set. On average, 81% of the correct classifications and an absolute error of 0.15 are obtained. In this case, the best *TP rate* category was High and the best *Precision* category was Low.

```
=== Run information ===
Scheme:       weka.classifiers.lazy.IBk -K 3 -W 0 -A "weka.core.neighboursearch.LinearNNSearch
-A weka.core.EuclideanDistance"
Relation:     cobitnuevo500-weka.filters.unsupervised.attribute.Remove-R1,3
Instances:    548
Attributes:   36
Test mode:    5-fold cross-validation

=== Classifier model (full training set) ===

IB1 instance-based classifier
using 3 nearest neighbour(s) for classification


Time taken to build model: 0 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         443               80.9872 %
Incorrectly Classified Instances       104               19.0128 %
Kappa statistic                          0.7066
Mean absolute error                      0.1552
Root mean squared error                  0.3249
Relative absolute error                 36.1977 %
Root relative squared error             70.1745 %
Total Number of Instances              548

=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   Matthews CC   ROC Area   Class
  0.75      0.036      0.93      0.75     0.83        0.751       0.924     LOW
  0.819     0.196      0.739     0.819    0.777       0.614       0.843     MEDIUM
  0.904     0.065      0.786     0.904    0.841       0.798       0.938     HIGH

=== Confusion Matrix ===

   a   b   c   <-- classified as
 159  53   0 |   a = LOW
  12 181  28 |   b = MEDIUM
   0  11 103 |   c = HIGH
```

Figure 7. Results of applying IBK with K = 3 by using 5-fold cross-validation.

In the case of MLP, it is verified that the best neurological network topology is that of a hidden layer with 19 neurons and the use of degrees of freedom, a learning speed of 0.3, and *momentum* or influence of previous weights 0.2, which are the results shown for the MLP of Tables 1 and 2.

5. Conclusions

This work aimed to assess organizational transparency in technology processes considering maturity levels of COBIT. The research carried out makes contributions to the existing scientific literature by establishing relationships between the performance of technological processes and organizational transparency within the framework of knowledge management, providing evidence of their importance for the sustainability and accountability of companies.

Using Data Mining techniques, it was found that monitoring and assessment of IT performance (MO1) is directly dependent on investment in monitoring and evaluation through internal controls (MO2), which is supported by the management of IT investment (PO5) where the transparency is low when the Quality Management (PO8) maturity level is ≤ 3 (the processes may be established but the use of control indicators are still at a nascent stage) and when the definition of the IT Strategic Plan (PO1) responds to a pattern that is not sufficiently defined and depends on individuals' knowledge.

It was also evidenced that the monitoring and assessment of internal control (MO2) depend on the organizational capacity to manage problems (DS10) and that the transparency associated with technological processes is low when the Management of Risks (PO9) depends on individual knowledge with no defined processes in place, with risk control being initial with insufficient experience at the Project Management (PO10) level.

Therefore, four learning techniques were used to build a computational model with a decision tree approach. The decision tree shows the analyses connecting the different processes in a hierarchical way, classifying them as High, Medium, and Low according to the transparency level attributed. The connections found between technological processes and the analyses carried out allow a better understanding and targeting of the company's resources application priorities so as to achieve greater organizational transparency and knowledge management. In this sense, IT performance assessment and monitoring through internal controls are related to IT strategic planning and quality management, with the level of organizational transparency being low and medium when such processes are not well defined and have not yet been incorporated into the organizational capital but rather depend on individual knowledge.

The results of the research evidence the importance of improving the maturity of IT performance monitoring and evaluation processes to increase organizational transparency, for which it will be appropriate to establish quality controls over IT processes. A higher level of maturity in internal controls also has positive effects on the achievement of greater transparency, and companies are recommended to invest in control processes to reach better IT performance.

From the point of view of managers and business practitioners, this means that the improvement in the maturity of these processes by making them dependent, not on individual knowledge, but on institutionalized and organizational knowledge and well-defined governance processes, together with wider adoption of practices and experiences, produces an increase in the levels of organizational transparency and its reputational, financial, and accountability impact. Thus, achieving a higher level of transparency will depend on the intensity of resources and investments applied to knowledge management and on improving the maturity of technological processes through IT strategic planning and quality management. Likewise, the maturity of risk management processes and their integration into the organizational culture associated with project management also deserve attention from the management team with a view to increasing the level of transparency and reducing information asymmetries.

The quality of information and transparency ensure better ethical behavior and accountability of managers, supported by IT performance monitoring and evaluation processes, as well as internal controls based on strategic plans, risk management, and IT projects, which guide companies in maintaining proper corporate governance, financial sustainability, reputation, and responsibility to society.

Finally, it is important to highlight that this study has been able to assess organizational transparency through technology processes and contribute to better management of information, which reduces organizational risks, improves the governance structure, ensures financial and non-financial information with equal, appropriate, and efficient access, as well as timely information that builds trust among stakeholders.

The regional scope in the south of Brazil and the sectors of the companies on which the research was carried out do not allow the results to be generalized. It is also recommended to extend the research by conducting statistical analyses to confirm the results and find new findings.

For future studies, it would be interesting to direct efforts towards expanding the approach in an international way, comparing regions with different cultures in private and public organizations. In addition, with machine learning models like the one presented here, it is possible to anticipate evaluations and therefore better target organizational investments in technology processes that generate more transparency in their activities.

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