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Technology entrepreneurship:

how do firms leverage data science as a basis of decision-making – a case study

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ABSTRACT

This paper presents a case study on how an established organization exploits technological opportunities by encouraging technological entrepreneurship initiatives, focusing on the organizational level of analysis. In a qualitative approach, this descriptive case study investigates how a multinational company in the mining sector uses new technological aspects related to Data Science to improve its decision-making process in several phases of its production process. The sources of evidence used were analytical solution documents, data architecture recommendations and solutions, data usage policies, training reports, data usage reports, data access reports, and memos. The data analysis was organized around the core document "Recommendations for data architecture and solutions," in an analogous way to the notion of literary inscriptionas a methodological principle. The documents were checked to employ word/phrase analysis, systematic comparison, and integration. This paper contributes a better understanding of corporate innovation ecosystems and to academic debate of corporate innovation ecosystems incorporating technology entrepreneurship initiatives.

Keywords: Entrepreneurship; Technology Entrepreneurship; Data Science; Decision-Making.

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1 INTRODUCTION

Technology entrepreneurship is a hotly debated scientific topic that has attracted researchers and policymakers (Mosey et al., 2017) and has been understood as the interface between entrepreneurship, innovation, and technology transfer (Ferreira et al., 2015, Urbano et al., 2018).

Entrepreneurs are featured as catalysts of new ideas and as leaders who put these ideas into practice, oriented toward the generation of social and economic value (Baumol 2005), in line with the classical approach to entrepreneurial innovation proposed by Schumpeter (1934).

Technology transfer, in turn, is associated with techniques and tools that allow organizational and individual know-how to be shared among companies, individuals, and other economic agents (Ferreira et al., 2015).

Technology transfer can occur between and within organizations. Thus, the dynamics behind such processes have drawn attention from researchers at different levels of analysis: individual level (e.g., Nacu & Avasilcai, 2014), organizational level (e.g., Beckman et al., 2012), and systems-level (e.g., Alotaibi & Zhang, 2017).

This paper focuses on the organizational level of analysis (i.e., the influence of resources and capabilities on the development of technologies/innovations). Objectively, the paper presents a case study on how an established organization exploits technological opportunities by encouraging technological entrepreneurship initiatives.

From this objective, the research question can be summarized as: **how do firms use the new technological aspects linked to Data Science to improve the decision-making process of its productive process?**

This research hopes to contribute to the academic debate of corporate innovation ecosystems incorporating technology entrepreneurship initiatives.

This paper is organized as follows: the following section (2) presents a review of the literature about Entrepreneurship, involving the topics of technology entrepreneurship and intrapreneurship. Section 3 offers the topic of Data Science and Artificial Intelligence. Section 4 describes the methodological design, including data collection and analysis. Section 5 describes the case study. Finally, section 6 presents concluding remarks.

2 INTRAENTREPRENEURSHIP AND TECHNOLOGY ENTREPRENEURSHIP

The concept of entrepreneurship is still not consensual in academia, although research on the topic is abundant and varied, as noted by Ferreira et al. (2017).

In general, the definitions of entrepreneurship are closely linked to the intrinsic characteristics of the individual who undertakes it (Ferreira et al., 2017), that is, the figure of the entrepreneur, who, for Schumpeter (1942), is responsible for driving economic development by introducing innovations that break with the status quo.

Meynhardt and Diefenbach (2012) define entrepreneurship by associating the term with the behavior of an individual who is inclined to take risks and act proactively in identifying and exploiting opportunities, destroying the economic order (Schumpeter, 1945) by introducing new products and services and bringing about changes in business and society (Hisrich & Peters, 2004).

Starting in the 1980s, studies were developed to understand the phenomenon of entrepreneurship within organizations (e.g., Miller & Friesen, 1983, Pinchot, 1985, Diefenbach, 2011). Since then, the supply of nomenclature to refer to entrepreneurial actions carried out within companies has grown, reaching four variations treated analogously.

Thus, intrapreneurship (Antoncic & Hisrich, 2001, Hashimoto, 2006, Kuratko et al., 1993, Nielsen, 2000) or corporate entrepreneurship (Burgelman, 1983, Covin & Miles, 1999, Hornsby et al., 2002, Zahra, 2005, Thornberry, 2003) refers to the entrepreneurial activity carried out by an employee, in the organization where he or she works.

Intrapreneurship can be understood as a sub-area of entrepreneurship (Antoncic & Hisrich, 2001, Hashimoto, 2009), in that the former is carried out in the internal environment of an existing organization, while the latter occurs in the marketplace and is associated with the creation of a new business (Angelo, 2003).

From this perspective, an intrapreneur is an individual who behaves in an entrepreneurial manner while an employee (collaborator) of an organization, being a simple employee in the words of Beaucourt and Louart (2000). In this sense, he is the one who acts in an entrepreneurial manner in a company to which he sells his labor force, not having, over it, the rights and duties of a partner or owner.

The term intrapreneurship, as a concept linked to behaviors or behavioral intentions related to the disruption of practices and ordinary aspects of existing organizations by their employees, was offered by Pinchot (1985) as an alternative way for the human resources of organizations to be better used.

Understanding intrapreneurship in line with Pinchot's (1985) concept, Antoncic, and Hisrich (2001) pointed out eight different interrelated elements that constitute the multidimensional concept of intrapreneurship, according to its effects: conceiving new ventures, creating new businesses, innovating in products/services, innovating processes, self-renewal, risk-taking, proactivity, and aggressive stance to compete.

This perspective made it possible to solve the false dichotomy between being an entrepreneur or being a collaborator (Hashimoto, 2006) since, from this perspective, it was possible to understand that any employee can act as an internal entrepreneur.

Pinchot (1985) emphasizes the relationship between organizational success and the creation of a corporate environment and of mechanisms favorable to the practice of intrapreneurship, indicating that there is a tendency for successful organizations to become spaces that foster corporate entrepreneurship.

Taking the innovation theory offered by Schumpeter (1934) as a basis, Davcik and Sharma (2016) assert that organizations can generate competitive advantage and earn economic gains from making successful innovations and managing their resources innovatively.

Marcus and Zimmerer (2003) highlight the growing potential of the intrapreneur to contribute to organizational success in highly dynamic and highly competitive environments. For Meynhardt and Diefenbach (2012), intrapreneurship is a phenomenon related to organizational changes.

In short, intrapreneurs can promote innovations capable of generating sustainable competitive advantage for the companies in which they operate, identifying and taking advantage of opportunities (Woolley, 2010) to break with existing practices and creating value for the organization in which they work and for their respective customers, internally performing the Creative Destruction advocated by the Schumpeterian vision.

As suggested by Akgün et al. (2014), it is difficult for an organization to maintain its competitive advantage when it operates in an environment in which it experiences rapid changes in factors and numerous innovations brought about by accelerated technological advances unless it adapts promptly to such changes.

In this sense, the organizational ability to respond appropriately to environmental changes is related to the dynamic capabilities perspective (Teece et al., 1997) and the resource-based view (Barney, 1986, Penrose, 1959).

For Han and McKelvey (2008), the survival of the organization is directly related to its ability to develop dynamic capabilities, which, in the words of Teece et al. (1997), is related to its ability to develop, associate, and reconfigure internal and external capabilities according to the dynamism of its business environment.

Enterprises operating in globally competitive environments face strategic decisions related to technology development (Martin-Rojas et al., 2019), important to respond appropriately to changes in their business environment with innovations that make them competitive (Hitt et al., 2007).

Developing internally or acquiring externally innovative technologies and capabilities is a decision that involves trade-offs and risks, advantages and disadvantages, which organizations must consider aiming to ensure competitive advantage (Haro-Dominguez et al., 2010, Martin-Rojas et al., 2019; Zahra, 2008).

The mastery of technology and continuous learning processes within organizations are configured as innovative capabilities that enhance the development of new technologies, new knowledge, and the exploitation of innovation opportunities related to the formation of sustainable competitive advantage for the business (Alvarez & Barney, 2007, Haro-Dominguez et al., 2010, Martin-Rojas et al., 2019).

Garcia-Morales et al. (2014) point out that distinctive technological competencies are capabilities that the organization possesses that are important for the development and/or improvement of products and services.

Technology integration figures as a core element of corporate entrepreneurship, being an essential organizational capability for the process of acquiring, using, and increasing technologies and knowledge, related to the commercial exploitation of potential innovations (Drent & Meelissen, 2008, Martin-Rojas et al., 2019).

For technology integration to occur effectively, the organization must promote and ensure the existence of a culture and organizational climate conducive to intrapreneurship, in which individuals are encouraged to take risks and take ownership of new knowledge and technologies, having their actions and creativity rewarded (Drent & Meelissen, 2008, Martin-Rojas et al., 2019, Wilden et al., 2016).

Organizations with an environment conducive to intrapreneurship can develop and explore new solutions and are more likely to gain a competitive advantage (Martin-Rojas et al., 2019, Wilden et al., 2016).

To operate in an intrapreneurial way, leaders and managers must act dedicated to provoking organizational changes, performing and fostering the identification of opportunities to innovate in products, services, processes, ventures from existing resources and capabilities in the organization (Martin-Rojas et al., 2019, Camelo-Ordaz et al., 2012).

Another condition of intrapreneurship is that the organization provides resources and infrastructure favorable to Innovation and sustains this activity by managing its processes (Terra, 2012), assuming the risks, and appropriating the intellectual rights and gains related to it (Maier &; Zenovia, 2011).

Among the resources related to fostering intrapreneurial activity are Information and Communication Technologies (ICT), with high potential to contribute to Innovation and increase efficiency and organizational performance (Yunis et al., 2017).

Due to the ICT capability to support strategic decisions of organizations competing in dynamic markets with intense rivalry (Yunis et al., 2017), different authors relate these technologies with dynamic capabilities that can generate value for the firm that owns them (e.g., Cepeda & Vera, 2007, Kindstrom et al., 2010, Sandberg, 2013, Tian et al., 2004, Urbano et al., 2018, Wang et al., 2010).

Entrepreneurship-inclined organizational orientation is an important dynamic capability that contributes to developing innovations related to technological entrepreneurship and business competitiveness (Urbano et al., 2018).

As resources that generate dynamic capacity throughout their use, ICT are employed in the creation, integration, and enhancement of critical resources, contributing to the development of new: products and services, processes, business models, marketing and customer relationship systems, and management methods (Yunis et al., 2017).

Urbano et al. (2018) highlight the importance of the business environment in fostering entrepreneurship and breakthrough technological innovations, drawing attention to the implications of regulatory conditions of the innovation ecosystem on stimulating entrepreneurial activity.

This context, the literature on technology entrepreneurship is generally organized around two streams. One involving the commercial exploitation of public research and employment of academic research (Trune & Goslin, 1997, Wright et al., 2004, Yuan & Jia, 2005); the other, related to studies linked to high-tech entrepreneurship (Bruton, 2010, Kenney & Burg, 1999, Zhang et al., 2012).

Technology entrepreneurship, a term initially proposed by Shane and Venkataraman (2000), is related to seizing opportunities for technological innovations linked to value exploration through the creation of a new business or the design of a venture in an existing company (Hindle & Yencken, 2004, Hisrich et al., 2016, Lei et al., 2016).

For Bayers et al. (2014), technology entrepreneurship is related to the ability to make principled decisions and a business management style inclined to identify technology-intensive opportunities of great commercial potential through its capabilities.

In light of Bailetti's (2012) propositions, technology entrepreneurship can be understood as an investment project to create and capture value from the integration of strategic resources and heterogeneous assets interrelated with the generation of technological and scientific knowledge.

3 DATA SCIENCE AND ARTIFICIAL INTELLIGENCE

The use of data and statistical techniques to support decision-making is not new to the business world. The decision-making process has been migrating over the years from a scenario typically based on intuition, experience, tacit knowledge, and pattern recognition (e.g., Behling & Eckel, 1991; Brockman & Anthony, 1998; Simon et al., 1987) to an information-based scenario. Some authors argue that intuition is a mode of information processing that comprises sensory, cognitive, and affective elements and results in direct knowledge without conscious reasoning (e.g., Dhar, 2013; Parikh et al., 1994; Petitmengin-Peugeot, 1999). Managers are more likely to use intuition to solve unprecedented, ill-defined problems, usually associated with non-routine situations (Parikh et al., 1994); however, when available, information from past circumstances is an indispensable tool for decision-making (Prüfer & Prüfer, 2020).

Scholars argue that the practice of basing decisions on information and not purely on intuition is more effective (Provost & Fawcett, 2013). It would not be giving up intuition but expanding knowledge of the environment and the situation that presents itself, intending to increase success in decision-making. The recent rise of big data and artificial intelligence (AI) is changing markets, organizations, and societies. Expressions such as Industry 4.0, Internet of Things, Machine Learning are increasingly common in the business world and are closely linked to analyzing large volumes of data (Moura et al., 2018), also expressed by the term Data Science.

Data science refers to a set of fundamental principles that support and guide the extraction of information and knowledge from data (Provost & Fawcett, 2013). Science implies knowledge obtained through systematic study. Therefore, it would be a systematic process that builds and organizes knowledge in testable explanations and predictions (Dhar, 2013).

Data science involves the analysis of data through statistical and artificial intelligence techniques and their role in inference and consequent decision-making. The use of data, statistics, and artificial intelligence would not be new enough to forge this new term. Data science differs from statistics and other traditional disciplines. The main difference is the increasingly heterogeneous and unstructured data, such as text, audio, images, and videos, often coming from networks with complex relationships between their entities (Dhar, 2013). The terms data science, machine learning, and data mining are often used interchangeably (Kelleher & Tierney, 2018).

The data used in the analysis can come from different sources such as corporate systems, social networks, shop floor data, among others (Moura, Franqueira & Pessin, 2021). These can be correlated through special techniques in order to obtain inferences. Several techniques are applied to data science that extracts knowledge through different technologies (Prüfer & Prüfer, 2020).

Data science encompasses the capture, cleaning, and transformation of structured and unstructured data and the use of big data technologies to store these large volumes of data (Kelleher & Tierney, 2018). As for the techniques, the main ones include generalization, characterization, classification, grouping, association, evolution, pattern matching, data visualization, and meta-rule-guided mining (Liao et al., 2012). The application of data science is used to obtain different information, such as identifying groups, associations, anomaly detection, classification of things, and predictions (Kelleher & Tierney, 2018).

Among the techniques, the application of artificial intelligence (AI) stands out. The term artificial intelligence emerged in the late 1950s to build hardware and software capable of reproducing human intelligence. Years later, developments advanced in the field of engineering associated with pattern recognition, motion control, and data pattern identification to make predictions, hypothesis testing, and decisions, had as one of the main milestones the development of the backpropagation algorithm in the 1980s by David Rumelhart (Jordan, 2019).

Researching and building systems in document retrieval, text classification, fraud detection, decision support systems, recommendation systems, personalized search, and social media analytics have been great successes and have boosted large companies. Data science uses computer science and the available computational capacity by adopting statistical methods guided by AI algorithms. Cloud computing, for example, is one of the pillars that has enabled the analysis of an increasing volume of complex and unstructured data, offering multiple computational units, with high-performance computing and large data repositories (Moura et al., 2018).

Artificial intelligence allows algorithms to learn from data and generate models that associate hundreds of dimensions far beyond human capacity. These models are automated and connected to data sources and Application Program Interfaces (API) in order to collect and process large volumes of data (Prüfer & Prüfer, 2020), usually presenting their results in presentation tools and dashboards or interacting directly with other systems (Moura et al., 2018).

One of the most well-known and applied branches of artificial intelligence is machine learning (ML). ML includes techniques and algorithms that learn without programming and explicit rules. ML algorithms can adapt to perform intelligent activities, similar to human cognitive functions (Taddy, 2018). The three most applied techniques are supervised, unsupervised and semi-supervised.

Supervised techniques create mathematical models that learn and improve over time. AI models are applied (e.g., neural networks) to obtain results such as classification and clustering (Moura, Franqueira & Pessin, 2021). It compares an established model to validate data patterns and relies on training with previously observed labeled data.

Typically, algorithms learned the relationships between observed inputs and desired outcomes. Depending on the type of data, regression and classification techniques (decision tree, for example) can be applied (Prüfer & Prüfer, 2020).

Deep Learning (DL) is a supervised algorithm that extracts information from complex and multidimensional data, such as images. DL uses neural networks that simulate human neurons specially applied to derive patterns from non-linear processes. It employs consecutive layers of information processing stages hierarchically to classify patterns and learn resources and representations (Moura, Franqueira & Pessin, 2021).

Unsupervised techniques do not require training data and generally use statistics and methods such as clustering. The observations are then approximated to specific groups. An approximation is often analyzed using equality or inequality scores, Euclidean distance functions, or another type of function. In contrast to supervised learning, there are no explicit target outputs associated with each input; instead, the unsupervised algorithm brings in previous biases about which aspects of the input structure should be captured in the output (Reddy et al., 2018).

Semi-supervised techniques (SSL) use inference tests to verify whether or not part of the data agrees with a given statistical model (Moura, Franqueira & Pessin, 2021). The primary purpose of SSL is to overcome the disadvantages of supervised and unsupervised techniques. Supervised learning requires a massive amount of training data to classify test data, which is expensive and time-consuming. Unsupervised learning does not require any labeled data and groups the data based on similarity in the data points using the clustering or maximum likelihood approach. The main problem with this approach is that it cannot accurately group unknown data. To overcome these problems, SSL can learn from a small amount of training data, label the unknown (or) test data, and create a model with few patterns (Reddy et al., 2018).

Companies can use the techniques used by data science to improve access to information, leverage intrapreneurship, and improve decision-making. To this end, companies need to create a strategy to make this data available to the right people at the right time and with the right computing resources.

4 METHOD

In a qualitative approach, this descriptive case study investigates how a multinational company in the mining sector uses new technological aspects related to Data Science to improve its decision-making process in several phases of its production process.

The descriptive case study was chosen as the research method because it allows the researcher to capture and describe the complexity of real-life events (Yin, 1994).

The consistency supported this predilection noted between the way the research would evolve and the main aspects of the case study method (Yin, 2001): phenomenon examined in its context, data collected from multiple sources, one or few elements being examined, no controls or manipulation being used, focus on a contemporary event, and results are heavily dependent on the integrative capacity of the researcher.

The sources of evidence used, in order to obtain several measures of the same phenomenon, creating conditions for data triangulation during the results analysis phase, were:

- analytical solution documents;
- data architecture recommendations and solutions;
- data usage policies;
- training reports;
- data usage reports;
- data access reports; and
- memos.

The data analysis was organized around the research question "how does the organization under analysis use new technological strands linked to Data Science to improve the decision-making process of its production process?"

From this general question, from the core document "Recommendations for data architecture and solutions," in an analogous way to the notion of literary inscription (Latour and Woolgar (1997) as a methodological principle, the relationships between the various sources of evidence in the network of consulted documents were explored - in the process of evidence validation.

In other words, from the search for answers in the initial document, other questions arose that led to other data sources. The documents were checked to employ word/phrase analysis, systematic comparison, and integration (Strauss & Corbin, 1998).

5 CASE STUDY

This chapter presents a case study in one of the largest private companies in Brazil, established almost 80 years ago. It addresses how this organization uses new technological aspects linked to Data Science, encouraging technological entrepreneurship to improve its decision-making process in the most varied stages of its production process.

The firm is a multinational mining company with more than 130,000 employees, including employees and third parties, operating in the mining, logistics, energy, and steel. It is a publicly-traded company with a market value of around 83 billion dollars (B3, 2022).

The company has dispersed supply chain structures, implying production chains and facilities distributed in different countries with different business capabilities. These facilities have a large data generation capacity (Moura, Gonzalez, Franqueira, Maia Neto & Pessin, 2021). Despite being geographically distributed, the business niches are strongly correlated and highly dependent on each other. As a strategy, the company decided to centralize all its production management to gain productivity and synergy through holistic decision-making considering individual aspects of its operations.

For greater success in decision-making, the data from its various operations should be available to be correlated, taking into account not only aspects of productivity but also sustainability, environment, and safety of the people involved in the process. The data sources are varied and comprise shop floor data, operations management, planning systems, maintenance systems, supplies, human resources, energy, health, and safety.

One of the strategic decisions that the company had to make was to follow a centralized strategy, in which data analysis is done by teams specialized in data science, or general use, in which data is democratized. The decision was not to limit access to experts and allow any technical professional to access this data to improve their own decisions. The strategy enables stakeholders to play the role of data scientist whenever necessary, allowing all its technical staff to explore and extract information from these massive data, fostering entrepreneurial behavior within the organization.

For the data democratization strategy, several issues needed to be overcome, including collecting and unlocking data access, the availability of tools and training for interested people.

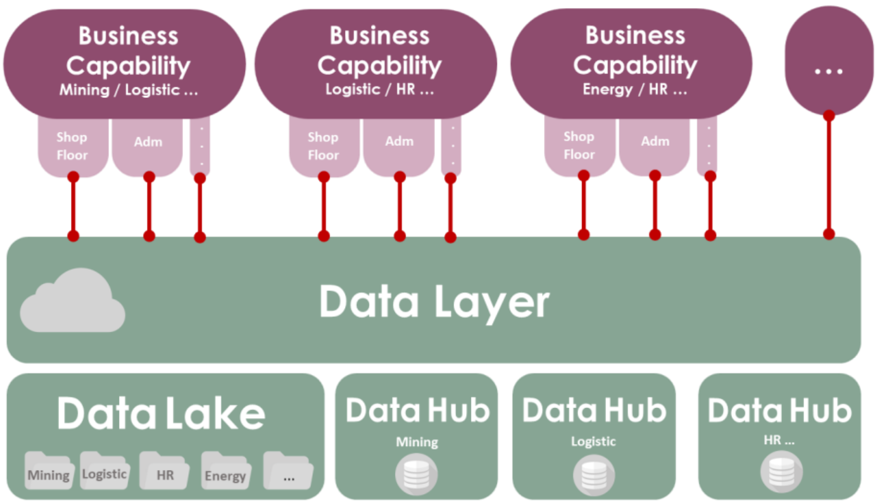
5.1 UNLOCKING DATA ACCESS

For data access to be unlocked, a valuable data collection structure was implemented in all phases of the operation and corporate systems in all locations where the company operates. The data already existed, but it was inaccessible for general use due to operation islands, information security barriers, and the risk that the use of the data could cause performance degradation in critical and productive systems of the company.

The solution was to replicate and ingest this data in centralized repositories in the cloud, called Data Lake and Data Hubs. The option to use cloud computing is due to the need for a large data repository, with native tools for analysis, and at a viable cost. Data Hubs store structured data in relational tables and repositories, such as SQL Server and SAP Hana, and can be created according to the business niche or specific interest. Data Lake is a high-volume, low-cost repository similar to storage that stores unstructured and semi-structured data, such as images, texts, and audios. The Data Lake can also be segmented by business capability or by some specific interest, as shown in Figure 1.

Figure 1

Data Collection and Centralization.



Source: Prepared by the authors.

This strategy aims to unlock access to data without jeopardizing operations. As a result, Data Twins (replicas) of the main assets, operations, and processes are made available that can be used in different scenarios.

5.2 ANALYTICAL PLATAFORM

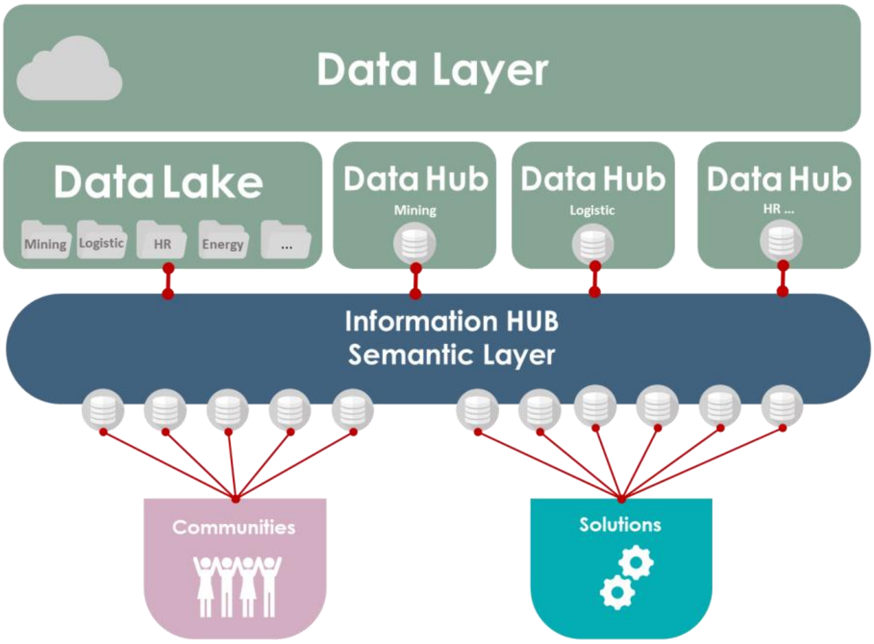
The analytical platform is a robust environment capable of handling large workloads and end-to-end management. End-to-end management improves the time-to-market of analytics projects and facilitates new capabilities and resources deployment. The analytical platform offers resources to two major groups: the data and analytics community and internal projects that produce solutions related to data analysis. The goal of the data and analytics community is to empower business decisions by increasing business intelligence through AI-based decision-making processes. To that end, it provides tools, capacity, and data without compromising cybersecurity. For projects, it enables the reuse and use of data and platforms to accelerate their completion and return value to the company.

The analytical platform comprises analytical repositories such as Data Hubs, Data Lake, and Information Hubs, including Data Warehouses, semantic layers, and advanced analysis tools such as Databricks, Machine Learning, languages, and frameworks using R, Python, Spark, and others. These tools can enable any AI techniques, such as supervised, semi-supervised, and unsupervised.

Information hubs offer data modeled as informational models aimed at reuse and business requirements of projects and products, that is, reliable data prepared for consumption by end-users and analytical solutions, with semantics, business metrics, and applied security, as illustrated in Figure 2. The analytics platform also offers presentation tools that can be used as information visualization dashboards.

Figure 2

Analytics Platform.



Source: Prepared by the authors.

The analytical platform is supported by data engineering teams whose function is to analyze, prepare and model semantic data layers that reduce the complexity in data treatment and facilitate the understanding and access of communities and projects of analytical solutions. This strategy enhances the use of data by reducing the need for users to have in-depth knowledge of database manipulation, offers a database that is treated and focused on specific needs, in addition to protecting source data from unintentional misuse.

The democratization of data access is based on the principle of reuse, in which Data Hubs and semantic layers are reused to accelerate access to end-user data. As operations are heavily dependent, the data tend to be correlated, which turns out to be useful in many situations.

5.3 TRAINING AND QUALIFICATION

The company also adopted an extensive training program, including graduate and master's programs, boot camps, and specific courses. The objective is to allow any employee to specialize in the widely used techniques and tools available. The company encourages the training of its employees and understands that the more people with knowledge and access to data, the greater the return of value through more informed decisions. Access to widely used tools is only possible after the employee complies with a minimum available training workload.

5.4 PLATAFORM USE

In 2021, 42,000 users from 26 countries accessed the presentation tools. Twenty-eight thousand data sets and 24,000 reports were created. More than 100 analytics projects were executed involving 48 different AI-related products involving 121 data scientists and engineers who created 179 models. The data catalog currently has over 300K assets, 3600 tables, and over 8TB of data. More than 1300 users accessed more than 300 GB of data present in the semantic layers created.

5.5 APPLICATIONS OF DATA SCIENCE

The three main applications of data science techniques were plant optimization, prediction of maintenance events, people safety, and decision-making support. In general, there are two phases in the application of the techniques. There are two momentums: model generation, when the models are trained, and the execution time at which models are subjected to real-time data. For the model generation, historical data from various sources are analyzed to select the technique that obtains the best precision and accuracy. By selecting the technique, a model is then trained for further use. On execution, the model is submitted to the data generated in real-time and responds according to its training. The historical data that support the creation of the models are available in the data layers in the cloud, but the real-time data cannot always be extracted from this same base, which implies specific implementations closer to the operations. This situation is more common in analytical solutions and is part of the projects' scope.

The optimization of operating plants aims to rationalize the use of supplies and, at the same time, reduce environmental impacts both for air quality and for effluents. Computational models support operators to choose the best operating points, acting directly on control loops. The models are based on historical data from sensors and actuators collected over the years.

The prediction of maintenance events aims to predict the need for preventive maintenance by predicting the wear and tear of equipment. For this application, it is necessary to correlate data from sensors present on the factory floor and maintenance orders present in corporate systems, such as ERP (Enterprise Resource Planning). These data generate mathematical models that can predict downtime events caused by wear and tear and equipment breakage, avoid unexpected production stops, and optimize maintenance planning.

Projects related to people's safety apply artificial intelligence techniques to detect events that could cause accidents. Among them, we can highlight the drowsiness detection to prevent operators from falling asleep and causing an accident, monitoring drivers' behavior when driving motor vehicles autonomous vehicles, monitoring equipment failures, and detecting anomalies through video analytics. Algorithms can detect these events in all cases, alerting the operator or a central monitoring system.

Support for decision-making has a broader range of action, as it can be carried out through specific actions by employees analyzing data relevant to their fields of activity or through projects that generate models to support strategic decisions. As all employees are potentially data scientists, they can develop private models supporting their micro decisions. However, these same data, correlated with others throughout the organization, can be applied to generate more complex models that support broader decisions, such as, for example, related to logistics, the acquisition of supplies, price of goods, among others.

6 DISCUSSIONS AND CONCLUSIONS

This chapter contributes a better understanding of corporate innovation ecosystems by describing how an established organization exploits technological opportunities by encouraging technology entrepreneurship initiatives.

The case study presented strategies for encouraging the application of Data Science technologies through data access and reuse (replicas available in centralized cloud repositories - i.e., Data Lake, Data Hubs, and analytic platforms) that enable a more conducive environment to decision-making; the case study does not favor generalization.

The shift from a centralized strategic orientation (in which specialized Data Science teams performed data analysis) to open access (in which any technical professional started to have access to data) proved to be fundamental. It boosted entrepreneurial behavior within the organization. This aspect aligns with the findings of Urbano et al. (2019), who identified positive effects on the levels of technology entrepreneurship in organizations oriented to constant absorption of technological inputs, i.e., their application in the organization's internal processes.

As part of the strategy, by retaining a team of data engineers to support the creation of semantic layers, the company has reduced the complexity in handling data by providing more focused views of the needs of each of the data communities and users. A focused view makes data analysis easier and allows users and solution designs to achieve results faster.

Equally important was the decision to implement the training program involving training, boot camps, etc., and to institute the employee's training as a requirement for access to the tools of broad use. This way, training is encouraged to understand that it is not enough to give access to data and analytical tools, but also the technical knowledge to deal with these data. A similar understanding is presented by Garcia-Morales et al. (2014), for whom the distinctive technological competencies represent the organization's capability to apply technological knowledge through structured processes to develop or improve products/services.

In light of this reasoning, we hope that researchers, policymakers, and practitioners in the field of technology entrepreneurship can drive the dynamics and growth of this particular research community. This is particularly relevant because of the ever-changing technological trends.

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Empreendedorismo tecnológico: como as empresas impulsionam a ciencia de dados como base para tomada de decião - um estudo de casoTitulo

RESUMO

Este artigo apresenta um estudo de caso sobre como uma organização estabelecida explora oportunidades tecnológicas incentivando iniciativas de empreendedorismo tecnológico, com foco no nível organizacional de análise. Em uma abordagem qualitativa, este estudo de caso descritivo investiga como uma empresa multinacional do setor de mineração utiliza novos aspectos tecnológicos relacionados à Ciência de Dados para melhorar seu processo decisório em diversas fases de seu processo produtivo. As fontes de evidência usadas foram documentos de solução analítica, recomendações e soluções de arquitetura de dados, políticas de uso de dados, relatórios de treinamento, relatórios de uso de dados, relatórios de acesso a dados e memorandos. A análise dos dados foi organizada em torno do documento central "Recomendações para arquitetura e soluções de dados", de forma análoga à noção de inscrição literária como princípio metodológico. Os documentos foram verificados para empregar análise de palavras/frases, comparação sistemática e integração. Este artigo contribui para uma melhor compreensão dos ecossistemas de inovação corporativa e para o debate acadêmico sobre ecossistemas de inovação corporativa incorporando iniciativas de empreendedorismo tecnológico.

Palavras-chave: Empreendedorismo; Empreendedorismo Tecnológico; Ciência de Dados; Tomada de Decisão.

Emprendimiento tecnológico: cómo las empresas aprovechan la ciencia de datos como base para la toma de decisiones - un estudio de caso

RESUMEN

Este artículo presenta un estudio de caso sobre cómo una organización establecida explota las oportunidades tecnológicas fomentando iniciativas de emprendimiento tecnológico, con un enfoque en el nivel de análisis organizacional. En un enfoque cualitativo, este estudio de caso descriptivo investiga cómo una empresa multinacional del sector minero utiliza nuevos aspectos tecnológicos relacionados con Ciencia de datos para mejorar su proceso de toma de decisiones en diferentes etapas de su proceso productivo. Las fuentes de evidencia utilizadas fueron documentos de soluciones analíticas, soluciones y recomendaciones de arquitectura de datos, políticas de uso de datos, informes de capacitación, informes de uso de datos, informes de acceso a datos y memorandos. El análisis de datos se organizó en torno al documento central "Recomendaciones para arquitectura y soluciones de datos", similar a la noción de inscripción literaria como principio metodológico. Los documentos fueron verificados para emplear análisis de palabras/frases, comparación sistemática e integración. Este artículo contribuye a una mejor comprensión de los ecosistemas de innovación corporativa y al debate académico sobre los ecosistemas de innovación corporativa que incorporan iniciativas de emprendimiento tecnológico.

Palabras clave: Emprendimiento; Emprendimiento Tecnológico; Ciencia de Datos; Toma de Decisiones.