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# TOWARDS DEVELOPING A DECISION SUPPORT SYSTEM FOR THE INDUSTRY 4.0

*Rumo ao desenvolvimento de um sistema de apoio à decisão para a Indústria 4.0*

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## ABSTRACT

The ability to swiftly modify and respond to developments in the business environment is essential for firms to be capable of functioning in the extremely competitive surroundings of the contemporary socio-economic context. The development of Industry 4.0 has given businesses the opportunity to become more competitive. The process of digital transformation of enterprises is referred to as Industry 4.0. It transforms the nature of business of a company drastically. The purpose of the study is to determine whether the data visualization techniques promote the decision support systems. The major aim of the research will be to investigate the features of the microsoft power BI. The research proposed the ideology of implementing the data visualization concept to the decision support system. A dataset of an enterprise was taken to implement the statistical analysis and to find the correlation among the variables. The research found the correlation of the variables along with the data visualization charts where the complex data is generated as bar graphs and it helps the stakeholders to make decisions. This research will cover the building of a business intelligence system utilizing Microsoft Power BI and the outcomes that were attained.

**Keywords:** Industry, Fourth Revolution, Decision Support System, Microsoft Power BI

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# RUMO AO DESENVOLVIMENTO DE UM SISTEMA DE APOIO À DECISÃO PARA A INDÚSTRIA 4.0

*Towards Developing a Decision Support System for the Industry 4.0*

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**RESUMO**

A capacidade de adaptação e resposta rápida aos desenvolvimentos no ambiente empresarial é essencial para que as empresas sejam capazes de operar no ambiente extremamente competitivo do contexto socioeconómico contemporâneo. O desenvolvimento da Indústria 4.0 proporcionou às empresas a oportunidade de se tornarem mais competitivas. O processo de transformação digital das empresas é conhecido como Indústria 4.0. Transforma drasticamente a natureza dos negócios de uma empresa. O objetivo do estudo é determinar se as técnicas de visualização de dados promovem os sistemas de apoio à decisão. O principal objetivo da investigação será investigar as características do Microsoft Power BI. A investigação propôs a ideologia de implementação do conceito de visualização de dados no sistema de apoio à decisão. Foi utilizado um conjunto de dados de uma empresa para implementar a análise estatística e encontrar a correlação entre as variáveis. A pesquisa encontrou a correlação das variáveis juntamente com os gráficos de visualização de dados, onde os dados complexos são gerados como gráficos de barras e auxiliam as partes interessadas na tomada de decisões. Esta investigação irá abordar a construção de um sistema de business intelligence utilizando o Microsoft Power BI e os resultados alcançados.

**Palavras-chave**: Indústria, Quarta Revolução, Sistema de Apoio à Decisão, Microsoft Power BI

## INTRODUCTION

For many years, business intelligence has enhanced many decision-making processes. Following the fourth Industrial Revolution, the discipline is probably going to undergo a transformation. The World Economic Forum brought attention to the emergence of this fourth Industrial Revolution during their 2016 annual gathering. The effect on manufacturing enterprises is being researched by scientists from all around the world. According to several studies, economic considerations, such as severe competition, are the main cause of these shifts. The second most important technological driver is product complexity, followed by social considerations, particularly end users' shifting demands and mass customization. This is due to the fact that the process of timely acquisition of information (using this information) is a highly challenging task taking into account the large size of the group and its geographic dispersion, the heterogeneity and the high number of key performance indicators (KPIs) followed and monitored on all operation sites.

It can be explained both by the fact that there is no proper communication process where its meaning can be conveyed and by the absence of a certain hierarchy through which the treatment and monitoring of all the KPIs of the group can be organized. On the other side, the inability to see the correlation between indicators or the comparison to the target value for a particular measure also makes it difficult to make decisions. As a result, time is wasted while evaluating information since it cannot be quickly deciphered because it has to be treated first. The current effort, which has taken the shape of a BI platform that will be described the subject of this article, appears in this setting. It is anticipated that this system's installation would foster a data-driven culture inside the company. In order to better understand how business intelligence and data analysis may help manufacturing businesses create value, as well as to pinpoint the key contributions of existing research and knowledge gaps in the field, the current study is developed.

### Fourth industrial revolution

The fourth industrial revolution (which can also be referred to as an industry 4.0) and the digital transformation itself both develop exponentially. The digital revolution is transforming the lives of people and their working environment radically, but the population still exhibits confidence in what Industry 4.0 is going to offer in terms of sustainability (Ghobakhloo, 2020). The latest tendency in automation and information exchange within the companies is Industry 4.0. Regrettably, a universal mechanism of gauging the readiness of an organization to Industry 4.0 is yet to be developed. The process of the digital transformation of enterprises is called industry 4.0. It completely changes the business of a company. As an example, the shift of the manufacturers to all these various activities going on within and beyond the industry has an effect on all the organizational roles. Particularly, the economic circumstances of the recent period of organizational incorporation of digitalization alter the consumer demand dramatically. The question of whether such digitalization of organizations is the fourth industrial revolution or not is an academic debate. It was initially created in Germany, and subsequently it travelled to other countries. The most important part of industry 4.0 is a production of so-called cyber-physical systems (CPS), the production that is made relying on the synthesis of heterogeneous knowledge and data (Sony & Naik, 2020).

### Decision support system

A DSS's functionality is determined by the application area, which is mirrored in the system's organizational framework. A DSS for slope must offer encouraging knowledge and recommend the much more plausible solution, or a collection of actions, that might improve the overall system performance for each nominal operating condition that might occur. In accordance with a straightforward decision-making process and expertise gained through practice, this should be done. In order to do this, ramp-up is viewed as a sequential process in which an operator performs a series of operations to fine-tune the system (Doltsinis et al., 2020).

## Contributions of the study

The word "research aim" describes the overarching objective or major goal of a research study. This research project aims at integrating some of the indicators in the supply chain into a system which will enable more information to be managed and transferred more easily and consequentially enable better decisions to be made. The following are the major contributions of the current study:

- A methodological approach was adopted along with several stages. As a result, the identification and documentation of the indicator trees of the key supply chain components and the relationships among these indications were carried out. In a subsequent step, Power BI data reports are used to implement all needs. The modeling and handling of the various data tables will serve as the foundation for this stage.
- The generated system was tested in the third step of this process in order to verify the architecture and confirm the outcomes.

Although they also contribute to strategic value generation, operational BI skills are closely tied to the development of operational value. Because of this, businesses should invest in assessing strategic value even if they simply use operational BI apps. This action will help the company become more aware of the circumstances while the business strategy is being carried out and will speed up its transition into Industry 4.0.

## 1 LITERATURE REVIEW

Sony & Naik (2020) has explored the key terminologies which can be applied to examine the fourth industrial revolution. The goal of the study was to understand and point out the key terms for evaluating the readiness of the fourth industrial revolution of an enterprise, the correlations which are observed among the readiness factors and the way in which the future studies consider the findings of the previous studies. The study employed a systematic literature review (SLR) as a methodology, where they discovered six different factors of readiness. The correlation among them was also found out. Being the first literature analysis of how businesses are preparing to respond to the upcoming Industry 4.0, it provides 17 research hypotheses that will be used in future by subsequent researchers going ahead to study more about Industry 4.0. Although the mandatory name of the trend is "Industry 4.0", only a limited number of companies understand exactly what it means. This article has helped companies determine the factors that should be given serious considerations prior to the use of Industry 4.0 in the company (Sony & Naik, 2020).

The article by Ghobakhloo, (2020) contributes to the sustainability literature by categorically defining the sustainability roles of Industry 4.0. To realize this, this research presents in the first place the architectural design of Industry 4.0 and addresses in it the most prominent design concepts and technological advances of Industry 4.0. In the study, the interpretive structural modeling is also employed in investigating the relationships that exist between different Industry 4.0 sustainability roles within the context of their environment. The results reveal that precedence relationships exist between some of Industry 4.0 sustainability functions, which are complex. Matrice d'Impacts Croisés Multiplication Appliquée à un Classement (MICMAC) analysis reveals the outcomes of the industrial revolution. These more distant socio environmentally sustainable outcomes of Industry 4.0, which made possible by more economically sustainable economic functions. This research helped Industry 4.0 decision makers in the both the public and private industries, businesspeople, and academics—better comprehend the sustainability possibilities that the tech transformation may present and foster closer collaboration to guarantee that Industry 4.0 fulfills its sustainability goals as efficiently, equitably, and as fairly as conceivable throughout the world (Ghobakhloo, 2020).

Before implementing Industry 4.0, organizations assess their readiness levels using Industry 4.0 readiness models. Although there has been several research on Industrial revolution 4.0 readiness models, there are various levels of preparedness. Moreover, the preparedness model has not been experimentally validated across other industries or forms of organizations. The goal of their study was to conceive the Industrial revolution 4.0 readiness model's aspects and then assess how important they are for manufacturers, commodities, large enterprises (LEs), and small and medium-sized businesses (SMEs). An exploratory sequential mixed method approach is employed in the investigation. 37 senior managers took part in phase one through a purposive sampling frame. In the second

stage, 70 top managers took part in an online survey. According to the study's findings, the Industrial revolution 4.0 ready model contains ten dimensions. Moreover, the relevance of the dimensions as they relate to various industries and organizational types is advanced (Antony et al., 2023).

The advanced sensor system of Industry 4.0 enables the use of algorithms to analyze data, foresee how this may play out in the future, and propose solutions to counteract the situation, which is beneficial to both manufacturing as well as service business processes. In this work, researchers evaluate the bibliography on data-driven decision-making in management and propose potential study paths for data-driven decision-making for the Industrial revolution 4.0 course of implementation. Researchers conducted a study of the literature on data-driven choice techniques for industrial uses with an emphasis on scheduled servicing for this research. According to their research of the bibliography, a growing percentage of data-driven decision-making techniques have been created expressly to take use of the abundance of sensor-generated information within the framework of Industrial 4.0. Succeeding support decisions may become more sensitive and able to accommodate precise and preemptive judgements as technological infrastructures and cloud platforms for data processing and storage proliferate (Bousdekis et al., 2021).

A crucial stage in the implementation or conversion of a manufacturing system is the slope of productivity. Such a system has unavoidably been calibrated and tuned in order to be completely functioning and produce at its highest return. In order to fine-tune the system properly, a complicated decision-making process is used, and extensive testing and experimentation are needed to identify the system behavior. In order to create an Industry 4.0 compatible Decision Support System (DSS) for human input, this study takes into account the potential of slope and presents a Cyber-Physical Systems method that utilizes data gathering, knowledge construction, and information harvesting. The suggested method uses offline learning with earlier acquired information and is deployed as an online DSS. Many tests have been conducted. In a micro size assembly station, several trials have been conducted, demonstrating the predicted advantages of the suggested DSS. Findings indicate that employing the DSS reduces the amount of nominal operating steps needed by approximately 40% (Doltsinis et al., 2020).

Ten years after the notion of Industry 4.0 was first introduced, digitizing the industrial sector remains one of the most difficult jobs for businesses, particularly SMEs. The absence of a plan and personnel capabilities is regularly cited in the literature as one of the main obstacles to the acceptance of novel business models. Calculating the preparedness factor allows for the avoidance of the high level of expenditures required and the impression of significant risks with ambiguous future rewards. This study introduces a unique preparedness factor computation approach based on decision support systems and production planning. By utilizing decision support systems and statistical approaches included into the model, the framework allows for the ability to define the best possible strategy plan for digitalization while minimizing the impact of human perception and quantifying important variables. This snipping method makes it possible to comprehend the process of switching to revolutionary tech business models, throughout this instance ones that are focused on the design process. An analysis of a metal machining industry's case study demonstrates the model's applicability and dependability (Trstenjak, et al., 2022).

Grocery shopping has revolutionized as a result of the sudden arrival of COVID-19 outbreak. By offering "no-touch" smart shipping methods for agri-food goods, supermarket retail outlets may address in-store cleanliness, safety, and quality problems. Smart packaging has the advantage of informing customers about the degree of cleanliness of a packed item without having an immediate touch. In order to avoid food waste during outbreaks, this article suggested a data-driven decision support system that leverages intelligent packing as a smart product-service system. The suggested methodology minimizes food waste and the quantity of denied clients while boosting the turnover of inventory and constantly adjusting pricing of packed sensitive products based on freshness level. A fictitious but accurate case study of a single item was used to evaluate the concept. The findings of this analysis demonstrated that the effectiveness of a grocery store supply chain during epidemics is highly impacted by stock capacity, quality dividend yield, fresh timeframe, and discounts (Kabadurmus et al., 2023).

In the contemporary socio-economic climate, firms must be able to swiftly adjust and react to developments in their corporate environment if they are to continue and function in highly competitive situations. The development of Industry 4.0 has given businesses the opportunity to become more competitive. I4.0 offers technology resources that make it possible to gather and store vast volumes of data at a cheaper cost, enabling the digitalization of businesses. This becomes a crucial consideration since information constitutes one of the most

essential tools for companies because it enables them to support event-based decision making. Yet, processing data and making it accessible to people in need are required in order to get genuine value from it and understand what it means (Marques, et al., 2020). The goal of the case study was to combine a number of supply chain indicators into a system that would allow for better information management and transmission, which would then improve the decision-making process. This article will cover the building of a business intelligence platform utilizing Microsoft Power BI and the outcomes that were attained.

Microsoft Power BI is going to be utilized to create a business Intelligence platform. This is made a significant parameter because information is among the most important organizational resources since it enables organizations to provide support in event-based decision making. Nevertheless, in order to derive actual value out of data and arrive at its meaning, it is essential to have it processed and, subsequently, exposed to the people who require it. Therefore, in the light of this contribution and goal, we identified that the development of the Industry 4.0 (I4.0) will enable organizations to become more competitive. With the organizations digitizing, the resources that were introduced to the organizations under I4.0, include the ability to collect and store a substantial amount of data at a reduced cost.

## 1.1 Data collection and tools

The data collected from the constructed database, which comprises four datasets and three pair-dataset queries, will be utilized as a data source to track manufacturing expansion globally while taking into account a number of factors that appear to have varying effects. Engineering reasons, particularly industrial ones, are seen to benefit from the monitoring duty (Shwab, 2016).

## 1.2 Sample description

Sample was obtained and the data was loaded to the power BI tool. The dataset seems as demonstrated below. Table 1 contains the first few rows of the data set of the North American Industry Classification System. 31,186 verified business locations are currently operating actively in this industry (Miller & Ellis, 2016). The dataset contains 11 different attributes. Further, in the next section the study demonstrates the correlation analysis of each attribute.

**Table 1 - Dataset of North American Industry Classification System (NAICS)**

| Geographic area name | 2022 NAICS code | Meaning of 2022 NAICS code | Meaning of Type of operation or tax status code | Number of establishments | Value of sales, shipments, receipts, revenue, or business done ($1,000) | Annual payroll ($1,000) | First- quarter payroll ($1,000) | Number of employees | Number of non- employer establishments | Non- employer value of sales, shipments, receipts, revenue, or business done ($1,000) |
|---|---|---|---|---|---|---|---|---|---|---|
| New Jersey | 53 | Real estate and rental and leasing | Total | 8,749 | 1,73,27,641 | 28,13,137 | 6,95,853 | 53,751 | 88,126 | 87,28,714 |
| Utah | 71 | Arts, entertainment, and recreation | All establishments | 923 | 11,81,370 | 4,00,679 | 1,12,916 | 20,749 | 10,618 | 2,09,372 |
| Oregon | 44-45 | Retail trade | Total | 13,879 | 4,94,81,054 | 48,31,509 | 11,66,028 | 1,87,402 | 23,636 | 10,13,200 |
| Arizona | 62 | Health care and social assistance | All establishments | 16,872 | 3,70,55,881 | 1,42,36,127 | 34,32,523 | 3,15,107 | 33,924 | 12,36,073 |
| Vermont | 54 | Professional, scientific, and technical | All establishments | 2,113 | 17,82,043 | 7,39,869 | 1,69,124 | 15,948 | 8,775 | 3,19,945 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | services | | | | | | | | |
| Oregon | 53 | Real estate and rental and leasing | Total | 5,644 | 46,49,574 | 9,02,806 | 2,13,936 | 26,016 | 30,433 | 29,87,792 |
| Wyoming | 71 | Arts, entertainment, and recreation | All establishments | 428 | 2,48,460 | 79,303 | 20,316 | 3,971 | 2,502 | 50,769 |

According to table 1, the first attribute is Geographic area name, where the most of the fields claim to be from the United states. 2022 NAICS code is given in the succeeding column, for each different NAICS code there is a unique purpose and meaning thus the title of the next column is Meaning of 2022 NAICS code which comprises of various records such as Real estate and rental and leasing, Arts, entertainment, and recreation, Retail trade, Health care and social assistance, Professional, scientific, and technical services, Real estate and rental and leasing and Arts, entertainment, and recreation (Oehlert, et al., 2022). Meaning of Type of operation or tax status code is one of the vital factors to be considered in a business organization and rest of all the attributes are numerical values which will be considered for the correlation analysis.

### 1.3 Data analysis

For simplifying the calculations, every tree is given by its indicators in table 2. The Number of establishments, Value of sales, shipments, receipts, revenue, or business done ($1,000), Annual payroll ($1,000), First-quarter payroll ($1,000), Number of employees, Number of nonemployer establishments and Nonemployer value of sales, shipments, receipts, revenue, or business done ($1,000) are chosen to run under the numerical or the statistical analysis.

**Table 2 - Trees and indicators**

| **Tree** | **Indicators** |
|---|---|
| Number of establishments | Est |
| Value of sales, shipments, receipts, revenue, or business done ($1,000) | V (emp) |
| Annual payroll ($1,000) | A_P |
| First-quarter payroll ($1,000) | F_Q_P |
| Number of employees | Emp |
| Number of nonemployer establishments | Non_emp |
| Nonemployer value of sales, shipments, receipts, revenue, or business done ($1,000) | V (Non_emp) |

The BPMN 2.0 software was deployed in the study for the statistical analysis and for the data visualization the microsoft power BI was implemented. As a result of that, the following table 3, tabulates the mean, median, standard deviation, minimum, and maximum.

**Table 3 - Descriptive statistics**

| - | Mean | Median | S.D | Min | Max |
|---|---|---|---|---|---|
| **Est** | 274.8 | 294 | 95.51721 | 85 | 409 |
| **V (emp)** | 455995.7 | 135049.5 | 702090.8 | 32593 | 2651600 |
| **A_P** | 113680.5 | 40977.5 | 142522.6 | 11176 | 477822 |
| **F_Q_P** | 26344.4 | 10001 | 32000.04 | 2778 | 110318 |
| **Emp** | 3300.95 | 2074 | 2770.076 | 749 | 9014 |
| **Non_emp** | 2455.65 | 2421 | 916.7064 | 992 | 4256 |
| **V (Non_emp)** | 42113.7 | 33760 | 28185.05 | 9073 | 105476 |

Using BPMN 2.0, an effective and reliable method to execute the data files refresh was designed and studied. This tool aided in the process of reflection and examination of the tasks at hand. By eliminating operations that do not provide value, the process has been enhanced via consecutive iterations (leading to a waste of time and resources). This procedure seeks to create a flow that enables effective coordination and communication amongst all the concerned parties.

## 2 RESULTS

A series of training sessions were given for all users throughout the course of the project to teach them how to use the tool and to explain why it is important to utilize it. The ability to create new reports (based on the data sets that have already been processed and posted in the Power BI Service) that are more reflective of the special and unique requirements of their job in the organization, as well as using the information posted by the Power BI reports, should also be called upon by the users. As all workers are accessing the same data sources that are available in the Power BI Service, information uniformity can be maintained in this way.

### 2.1 Pearson Correlation analysis

According to the empirical studies described in the following sections, variables having comparable impacts on the objectives show comparable evolutionary tendencies over time. In order to measure how similar evolutionary tendencies are, this article uses the Pearson correlation coefficient. It also creates an adaptive variable classification based on the Pearson correlation coefficients of the factors.

**Table 4 - Pearson correlation-based grouping**

| - | Est | V (emp) | A_P | F_Q_P | Emp | Non_emp | V (Non_emp) |
|---|---|---|---|---|---|---|---|
| **Est** | 1 | - | - | - | - | - | - |
| **V (emp)** | 0.672 | 1 | - | - | - | - | - |
| **A_P** | 0.882 | 0.708 | 1 | - | - | - | - |

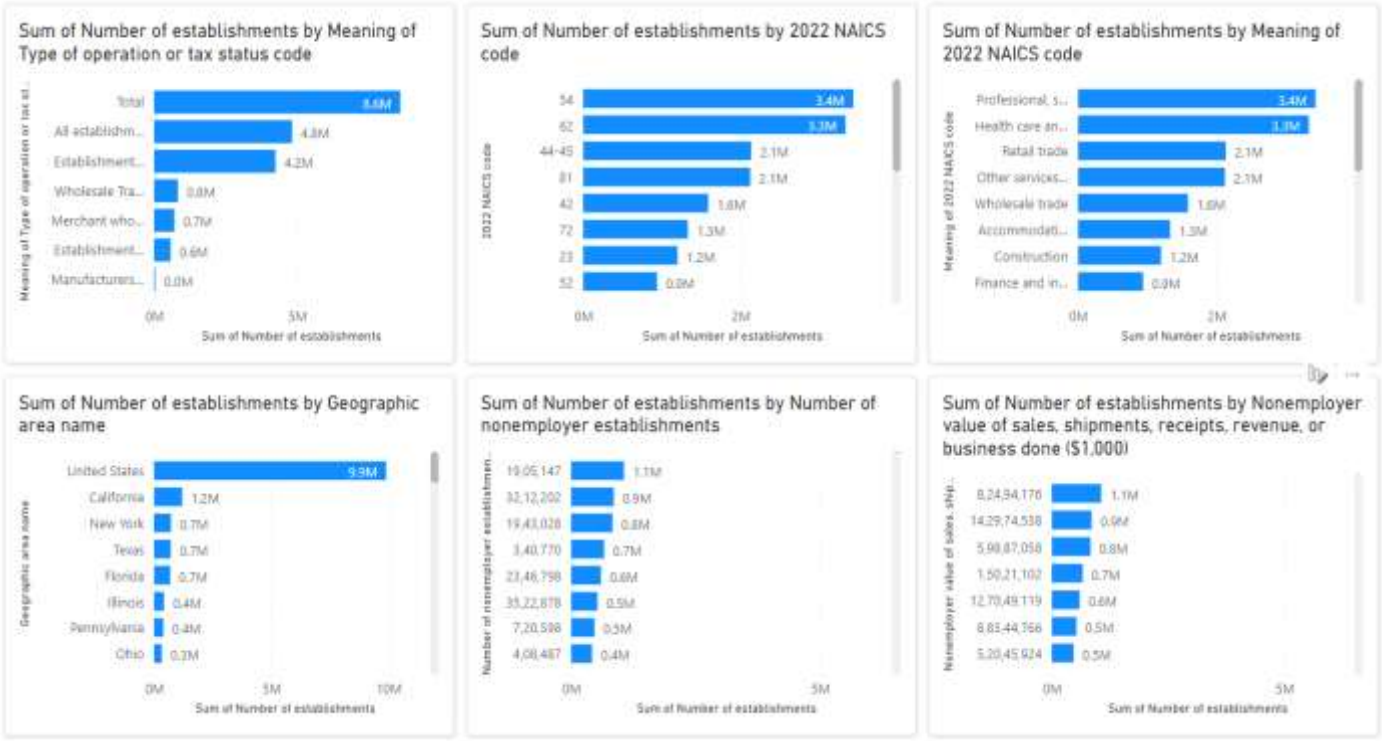
| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **F_Q_P** | 0.863 | 0.720 | 0.995 | 1 | - | - | - |
| **Emp** | 0.933 | 0.637 | 0.907 | 0.884 | 1 | - | - |
| **Non_emp** | 0.839 | 0.412 | 0.712 | 0.685 | 0.695 | 1 | - |
| **V (Non_emp)** | 0.749 | 0.429 | 0.620 | 0.603 | 0.569 | 0.882 | 1 |

Based on the correlation analysis, the number of establishments has a strong correlation with annual payroll, First-quarter payroll, Number of employees, Number of nonemployee establishments, and Nonemployee value of sales, shipments, receipts, revenue, or business done because the correlation coefficient value is greater than 0.7. Similarly, all the indicators are correlated with the trees. The values which are between 0.59 to 0.7 are considered as moderately correlated terms and if the coefficient is even less than 0.59, then it is negligible correlation or it is stated that there is no correlation between the factors.

## 2.2 Microsoft Power BI as DSS

A collection of software services, programmers, and connections called Microsoft Power BI makes it possible to turn information from data. The three key terms of the application are; Power BI mobile, Power BI desktop and Power BI service. These key components work collaboratively to produce interactive visualizations of data. From the obtained sample data, the figure 1 to figure 4 are the easy data visualization charts produced by Power BI.

**Figure 1 - Number of establishments**



From figure 1, it can be clearly observed that a user can easily analyze different indicators on a single tree, here meaning of type of operation, NAICS code, meaning of NAICS code, geographic area name, nonemployee establishments and values of non-employers' establishments are illustrated.

**Figure 2 - Meaning of type of operation or tax status**

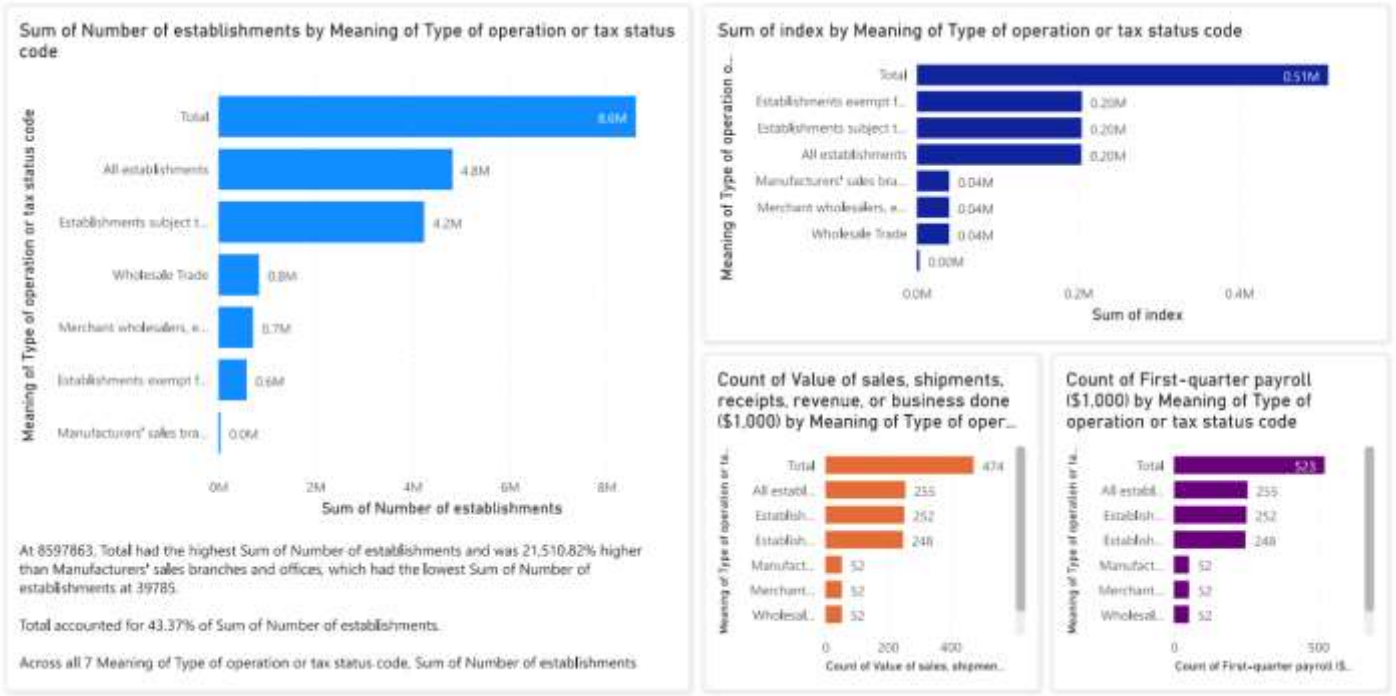
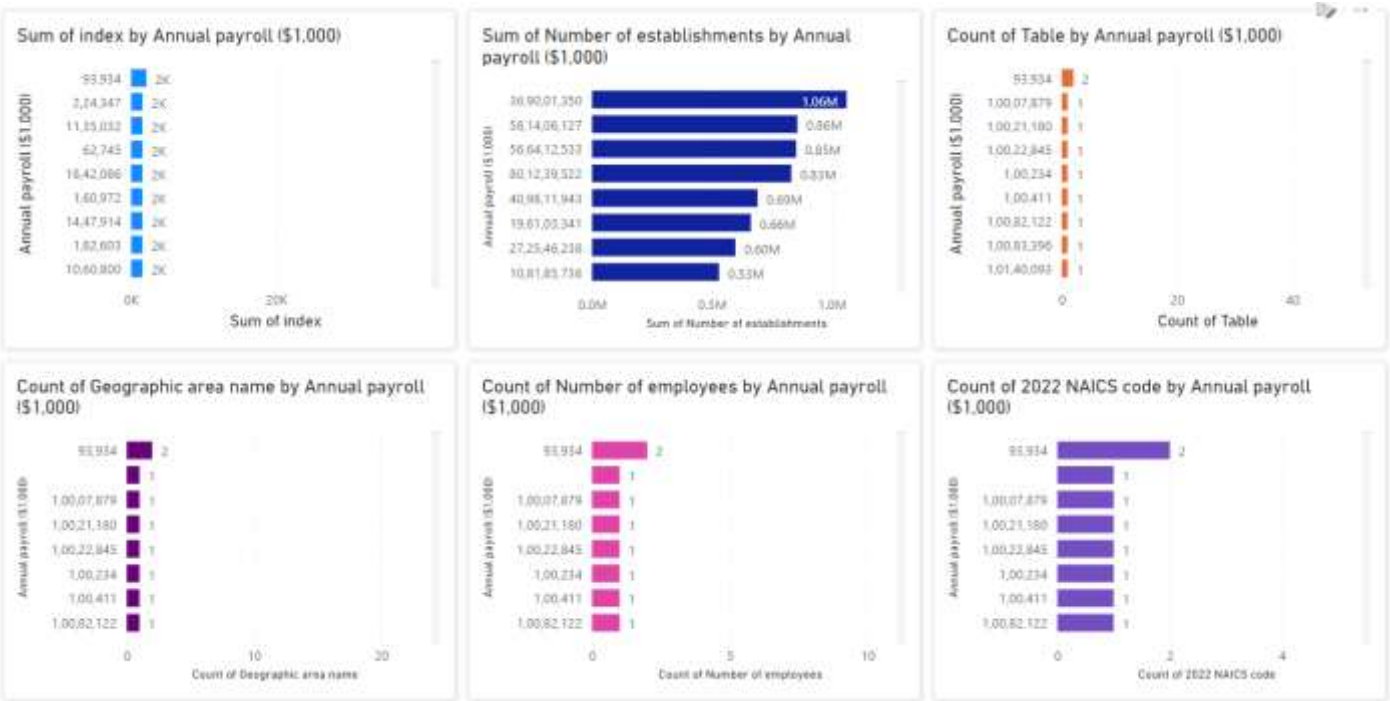



**Figure 3 - Annual payroll**




From the analysis of the visualizations, the decision-making process becomes easier and therefore it can be proved that data visualization tools like Power BI can be implemented as the decision support systems.

**Figure 4 - Geographic area name**


In this way, it is possible to provide the conclusion that such a BI tool as the one in question was capable not only of assisting the organization in the collection of this or that sort of important information regarding its previous and current state but also to assist in decision-making by taking an active part in the process of prioritizing crucial operational points that such organization could possibly pay enough attention to.

## 3 DISCUSSION

The indicator trees in the designed system display organizational data pertaining to the preceding monthly period in order to help the management of the company. As a result, the indicator tree reports must be updated monthly. Power BI provides a significant benefit when it comes to updating data tables since the various tables even have previously specified formatting masks, making updating all data much easier. In this situation, Power BI will automatically update all of the data tables by simply refreshing the relevant data sources. As personnel are no longer required to individually analyze all data files, this approach also significantly improves the pace at which data can be gathered (Marques et al., 2020). The adaptive variable grouping approach based on Pearson correlation is intended to adaptively categorize variables without using up more computer resources (Zhang et al., 2023). In an actual industrial use scenario, the decision support system technique is successful in resolving the machining quality and PdM task (Rosati et al., 2023). The meta-heuristic algorithms can be employed in the study as a part of improvisation (Abualigah et al., 2022).

### 3.1 Practical implications

The key problem that organizations are experiencing, however, is that such a large information structure may be processed in a timely manner and at a relatively low cost, so as to gain actual informational value. There is data in the context of digitization which is the foundation of I4.0. Data is one of the most important resources of the organization since it characterizes its real position and, consequently, contributes to the building of decisions on the basis of what has happened and what has been verified. Due to the advancement and growth of computing, networks and storage capacity, the possibility of gathering and storage of substantial rating of data at a more affordable rate has come to pass.

### 3.2 Theoretical implications

In terms of system upkeep, it's crucial to make sure that data reports are routinely evaluated because the requirements for information display and utilization might change over time. The involvement of a large number of people, positions, geographical locations, and operation places using this system is of utmost importance to ensure that the information provided is relevant and contributes and assists in making up decisions. To define and, over time, remove the waste in the processes of the creation of information and offer a higher value (i.e., the created information) to the user of the system, the improvement of the established system is needed persistently.

## CONCLUSION

A comprehensive collection of supply chain indicators from Super Bock Group may be integrated into a single central repository or database by using the designed solution based on Power BI. There are several quantitative methods that can be used to forecast and assist tactical and operational decision-making, but they cannot be used to support strategic decision-making. Exploratory qualitative approaches are frequently used to foresee changes, but they have limitations when it comes to addressing the When and Where issues. The ability to digest information, as well as decision makers' cognitive biases and beliefs, are constraints on the effectiveness of strategic judgements. In addition to having accurate knowledge of future standards for evaluating new technologies, it is crucial to have methods for overcoming information processing limitations, cognitive biases, and decision makers' beliefs.

### Limitations of the study

Several pieces of data used for this project's calculation of specific indicators are loaded into Power BI as active files from the areas of operations; thus, their structure may vary as a consequence of the unique requirements of these areas. The condition mentioned above may restrict automated data refresh since Microsoft Power BI follows a set of pre-established protocols for data processing. As a result, a recheck is required each month to ensure that these files are compliant and may be loaded into the software.

### Future scope

In future work, it is envisaged to move these files and documents to an information management that will ensure the integrity of data and architecture of the files, taking into account this restriction and attempting to simplify the task of updating database objects. It is recommended for Power BI to be directly linked to this database so that planned and automated data refresh may be performed. The time needed to upgrade the system will be reduced as a result.

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