Jurnal Ekonomi
Volume 13, Number 02, 2024, DOI 10.54209/ekonomi.v13i02
ESSN 2721-9879 (Online)
https://ejournal.seaninstitute.or.id/index.php/Ekonomi

Leveraging Data Analytics to Enhance Decision Making in Purchase Order Management: A Case Study in Aca Company

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Article Info	ABSTRACT
Keywords: Data Analytics, Decision Making, Purchase Order Management, Optimization	Using power analysis quickly can help companies make decisions. Regardless of the amount of data and its high level of diversity with big data analysis, this will still help employees in taking their tasks. Data analysis has a crucial role because it can help maximize resources and help determine the company's strategy to be able to estimate the reasons for making decisions. With a focus on optimizing purchase order management, my research at ACA Company delves into prevalent challenges in traditional systems, such as manual errors and delays. Embracing data-driven decision-making, ACA Company aims to enhance accuracy and timeliness in procurement through the application of data analytics tools. The data used is primary data provided includes details of purchase orders, including information about the region, location, order value, and issues that led to the cancellation. The data collection techniques in this study were observation, interviews, and documentation. The population in this study were all employees of the ACA company. The sampling technique used purposive sampling method. After the data is obtained, the next data processing uses a data analysis tool, namely Python. Based on the research results, it is found that with a culture of data-driven decision making, ACA Company can improve its purchase order management by identifying areas with high cancellation potential, prioritizing interventions, and understanding the financial impact of order cancellations. The integration of data analytics into the order management process introduced real-time dashboards, facilitated quick decision-making, and reinforced a culture of purchase order management optimization at ACA Company.
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INTRODUCTION

In its activities, companies are often faced with situations that require management to make decisions. The company is said to be successful depending on management decisions in choosing various kinds of alternatives that are most profitable for the company [1]. In the business world, making the right and accurate decisions is very important to maintain business continuity and development. One of the factors that can affect the success of decision making is the data used as a reference. Without accurate and relevant data, decision-making can be less precise and lead to strategic errors. Therefore, having a complete and up-to-date data reference is very important to ensure accuracy and precision in decision making in order management [2].

Decisions are the result of a problem-solving process and are solutions to questions related to the situation at hand. The process involves selecting alternatives from the various options available and ultimately ending the thinking related to the problem at hand. The decision itself is the result of decision making [3]. In conducting purchasing activities or implementing a project, companies collect data called purchase orders [4]. Documents recorded through purchase orders include payment, project implementation and also the date of recording.

Companies in using purchase orders as a record of a project, need to organize the number of purchase orders in order to know the development of the business being run from the company [5]. Project organization and maintenance can start from collecting purchase order data. After getting the data neatly organized, managers can use the data to make decisions. Purchase order management is a collection of attributes, the latest information about specific purchases that have been made. The data can be used by all entities in the supply chain process using available communication tools. The importance of purchase order management to meet the objectives of the procurement department to optimize the use of projects. Recording through purchase orders avoids errors in making transactions and also provides in-depth information that will be used in every recording of a process in the project [6].

Managing purchases is an important part of managing goods better. This means choosing to put a lot of money into the business. A business can lose money by working with the wrong source for the job if it does not have good purchasing controls [7]. By making purchase order management more effective and less costly, businesses can grow and expand while keeping track of their expenses and improving their processes. In short, managing purchase orders is an important part of the overall success of procurement and supply chain operations. It ensures that purchases are made quickly, easily, and cheaply, and that the supply chain is organized to meet the company's needs.

Previous research conducted by [8] stated that decision making is an important part of project management, which has a significant influence on the relationship between big data analysis and dimensions of project success. Thus, decisions can be made based on the experience and expert judgment of those involved in project implementation, which can be further improved by gaining insight into trends and clear information in big data. In line with research by Putra & Negara (2023) which states that technology for managing big data efficiently is still developing to continue to become more efficient and have better accuracy. The application of big data to decision-making systems can provide many benefits, for example reducing costs, improving the quality of services and products, speeding up the decision-making process, and making decisions relevant to real-time situations.

The novelty of this research is the case study of the ACA Company. The benefits of data analytics in improving decision making in order management are explored in more depth using data analysis tools, namely Python. With the importance of data analytics, the importance of this research is to support previous research. So the aim of this research is to explore the importance of improving decision making in purchase order management at ACA companies.

METHOD

Using quantitative research method means dealing with quantifying and analyzing variables to get results based on quantified analysis in the process [19]. Based on this definition, the author then takes a quantitative approach to answer research questions and objectives but certainly in a quantified way. Quantitative analysis here can answer such as how much, what happened, when and what will happen answered with numerical and also models.

The data used is primary data provided includes details of purchase orders, including information about the region, location, order value, and issues that led to the cancellation. The data collection techniques in this study were observation, interviews, and documentation. The population in this study were all employees of the ACA company. The sampling technique used purposive sampling method. Purposive sampling is a non-random sampling method where researchers ensure the citation of illustrations through a method of determining special identities that are suitable for the research objectives so that they can hopefully respond to the research case [20].

After the data is obtained, the next data processing uses a data analysis tool, namely Python. To conduct data analysis, the author takes a quantitative approach with the help of a programming language, Python. Python has many open source libraries that can be used to perform data analysis a[21]. By using Python as the main tool in performing data processing, analysis, and visualization. Python with many libraries and capabilities provides great power and capabilities in handling large datasets to carry out statistical techniques. In this sub-chapter, the author will explain what steps are needed to perform data analysis using Python.

Data Preprocessing

Recent studies suggest that data preprocessing includes many processes that can be selected depending on the datasets such as normalization, feature extraction and dimension reduction which can be selected for the purpose according to the data classification used [22]. The main purpose of preprocessing is to find out what features are informative to improve the performance of the classifier of the datasets.

Exploratory Data Analysis

Exploratory data analysis is an approach to see if the data we have can communicate with us by using formal modeling or using work that includes hypothesis testing [23]. Based on the reference there are several stage that will be used by the author to conduct data analysis which will be assisted by data visualization following these steps, namely:

Data Exploration

In this first stage, the author will explore the datasets owned regarding purchase order management at ACA Company. For things that are explored are how much data is owned and see what variables the data has. Things that can be considered again are whether there are missing values owned by each column because this can affect the

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process applied by Python. The use of data exploration can be assisted by several libraries by python such as Pandas and scikit learn.

Data Cleaning

Basically, data cleaning is a process where identifying and correcting errors in the dataset that can interfere with the model that will be created later [24]. When obtaining data by ACA Company, it is not certain that the data obtained can be processed immediately, but the author must check and identify variables as has been done in data exploration. The simplest example of errors that may occur is that there are columns that do not provide information or there are duplicate rows due to several processes such as exporting data.

Model Building

Model building is determining which model is suitable for use on data and adjusting to the research objectives by having existing data. Many models can be used as explained in chapter 2 regarding models such as correlation for extracting insights.

Present Results

This last stage in exploration data analysis is present results. Using the same reference, present results can use visualization because the human brain processes information faster using visuals such as graphs and charts [23].

Data Visualization and Interpretation

Data visualization is not only used in the Exploratory Data Analysis process but can be used in many places, especially with the help of programming tools such as Python. There are many uses of using data visualization in processing or showing the results of research. Deloitte on the website page reveals that there are 5 advantages of using data visualization, namely unlocking key values, identifying patterns, easy to understand, attractive or user-engaged, and displaying complex relationships [25]. In essence, the use of data visualization is to make data clearer and easier to see so that it can be more easily understood in the process and also easier for users to see in visual form.

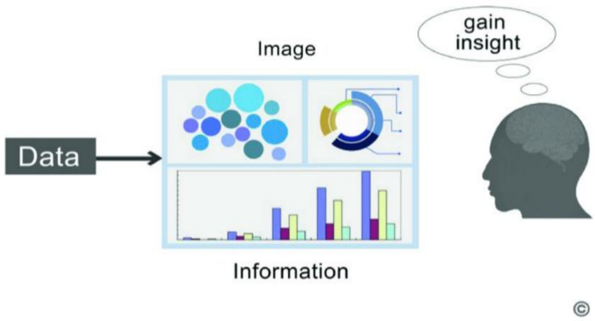

Figure 2. Process of Data Visualization
Source: (Li, 2020)

The figure above explains the process of data visualization as a transformation of data into information. How important data visualization is because the results will be used by the author to interpret what the analysis results mean and also what the data has. By definition, this process is a form of data representation in a visual way that can be

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understood by users by understanding what is meant by the visual of the data or the visual of the model developed based on references [26].

RESULT AND DISCUSSION

Analysis

The primary dataset provided encompassed purchase order details, including information on regions, sites, order values, and issues leading to cancellations. Through meticulous data processing and exploration, several key findings were discerned, which are visually represented below.

Distribution of Cancellation Reasons

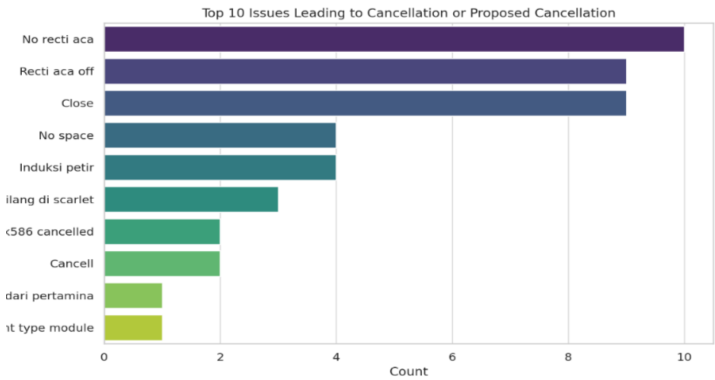

Figure 3. Distribution of Cancellation Reasons

The bar plot above shows the top 10 problems that cause order cancellations or are planned to be canceled based on the data owned by the company. Issues such as "No Recti ACA" are the most common issues for cancellations or proposed cancellations. This dominance shows that there is a systemic challenge to the issue that resulted in the order being canceled. Rectifier availability issues indicate potential shortcomings in training and coordination to handle specific issues. ACA rectifiers off, which also means issues in handling rectifiers owned by the ACA company, is the second issue for order cancellations. These indications indicate that although the problems are significant, each problem has different root causes that must be taken care of.

Problems that exist in the ordering process can be beneficial to investigate based on specific region sites or external factors such as the geographical conditions of the region owned by the company (especially Lightning Induction which translates to "Lightning Induction"). Lowering the number of issues to ten suggests that despite the large number of issues for order cancellations there are some major contributors to the problem. This pattern can indicate the Pareto principle or the 80/20 rule where a minority of causes can be the majority of the outcomes.

The many differences that occur in the causes of order cancellations indicate that there is no single operational solution that can solve all problems immediately. Different solutions and answers are needed for different challenges. For example, the rectifier problem that ACA Company has requires technical interventions or system upgrades

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where problems such as No Space are related to existing space problems owned by the site in operating in certain regions.

Recognizing and also understanding how often issues occur provides an opportunity to intervene proactively. Regular monitoring can identify some issues before they become more frequent, regular interventions can provide a delay before they become major challenges.

Descriptive Statistics of Potential Lost Value from Cancelled Orders

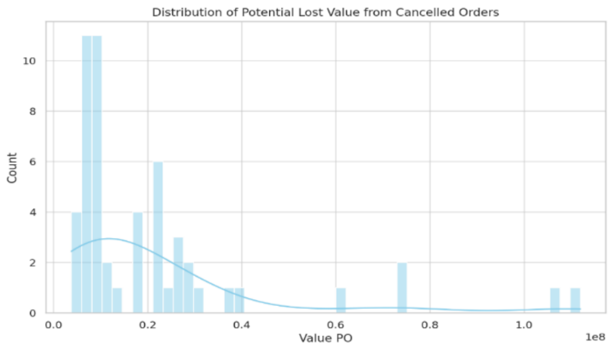

Figure 4. Results Statistics of Potential Lost Value from Cancelled Orders

The histogram above illustrates the distribution of potential lost value that occurs from canceled orders. The distribution of the visual shows that the condition is right-skewed, this indicates that although most of the canceled orders are orders that have low value there are also some canceled orders with higher potential value.

The skewness implies that most of the canceled orders are those with low value, but some of the canceled orders are high value orders that can provide potential value to the company's revenue or financial impact. The peak in the histogram distribution describes the most frequently canceled orders in a particular value range, which is close to the left end. This can be an indication that some products or services experience frequent cancellations. The long tail on the right side of the histogram indicates that there are high value orders that are canceled although not as often as those on the left side. The tail end can be considered as outliers but because it is crucial as a representative of potential revenue loss.

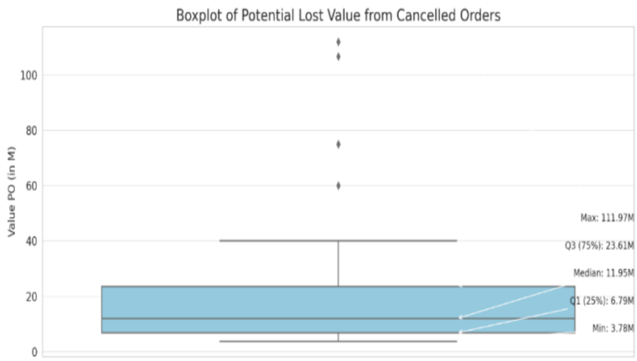

Figure 5. Boxplot of Potential Lost Value from Cancelled Orders

The mean or average value of the cancelled orders is significant, but due to the

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skewness of the distribution, the median of the cancelled order value data is considerably lower than the mean. This indicates that the large scale of the value of the cancelled orders increases the average value of the data distribution. The standard deviation of the data on canceled orders is quite large. This indicates a wide variability in the value of canceled orders. This wide variation is not limited to a particular segment but is spread over a wide range of orders.

Potential lost revenue in order cancellations is not evenly distributed. Although the majority of cancellations occur on orders that have low value, cancellations that occur on orders that have high value can provide financial risk. The financial impact experienced in the purchase order process does not only talk about the number of cancellations that occur but also tells about the value associated with the data. Addressing the reason behind high value orders that are canceled can significantly increase mitigation of potential revenue loss. Regular monitoring and segmenting orders based on value can provide interventions and strategies to stakeholders, especially on high value orders.

Regional Analysis of Cancelled Orders

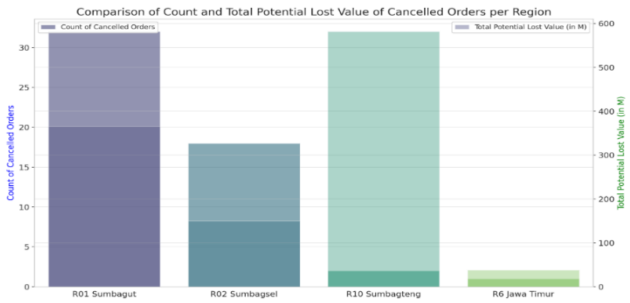

Figure 6. Result of Analysis of Cancelled Orders

The graph or figure above illustrates the clear differences in cancelled orders in the context of the count of cancelled orders and also the lost value that occurs in the regional sector. Some regions, despite having a lower number of cancellations than others, have a higher potential lost value (especially in R10 Sumbagteng). This indicates that although regions may have a smaller number of cancellations, cancelled orders may have a higher value.

The opposite also occurs in the region that has a higher number of canceled orders but has a lower total lost value (R02 Sumbagsel), indicating that orders that experience cancellations in the region are typically lower value. Regions such as R01 Sumbagut become very clear to be dominant in both aspects, namely the number of cancellations or total lost value in the region. This provides strategies that can be specific targeted interventions in this region to address the root cause of any cancellations in the region.

In summary, not only the number of cancellations is important but the value of the order is also important to analyze. Regions that experience fewer cancellations can still have a significant financial impact if the orders that are canceled in value have a higher value.

Diverse strategies are needed for different regions. For regions that have a higher number of cancellations and low value can be focused on improving operational efficiency.

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On the other hand, regions that have few cancelled orders but high value can be given personalized handling of the quality of existing goods.

Representing data simultaneously in terms of quantity and total lost value provides a holistic view of the financial and operational issues faced by each region. This underscores the importance of resolving issues in terms of order volume as well as the value of cancellations. In essence, to increase the revenue and efficiency of the purchase order process, it is crucial to consider the frequency and financial implications of cancelled orders across different regions.

Furthermore, the author analyzes in a deeper form not only at the region level but up to the level of sites that experience cancellations. The author sorted up to the Top 10 Sites that experienced cancellations to find out what happened at the site level. This can provide insight from the data that has been processed by the author.

The fact that the same issues can dominate at sites that experience a lot of cancellations is important to look at concentrating on the many challenges that occur. Addressing frequent issues can potentially provide ACA Company with good purchase order improvements across all sites, especially those with frequent cancellations.

By knowing the significant contribution of the ten sites that experience frequent cancellations, specific interventions can be given to these sites and can have a positive impact on the overall performance of ACA Company. While a broad strategy is important, it may also be beneficial to understand the specific sites to know and also understand if there are different challenges and constraints experienced so as to provide more tailored solutions. In summary, understanding the specific challenges of high-impact sites and addressing their primary concerns can be a pivotal step in reducing overall cancellations and improving operational efficiency.

Harnessing Analytical Findings for Optimal Decision Outcomes

Data analysis that has been carried out through a gradual process serves as a foundation in guiding strategic initiatives that are tailored to the existing processes at ACA Company. By conducting a deeper analysis of the data owned regarding Purchase Orders, especially regarding order cancellations and their causes, the author found patterns and trends that were previously unseen by the company. These findings represent what is happening in the company's operations, making it a strength that ACA Company can improve and improve the inefficiencies that occur in the purchase order process.

In the scope of decision making, data driven insights can provide stakeholders with comprehensive information that can help them to strategize appropriately. For example, knowing which region or regions have a higher potential for order cancellations so that they can prioritize interventions that are reinforced by which cancellation reasons are most common. As a company transitions to an era where monitoring a situation is important, this analysis provides knowledge on a responsive and informed approach to decision-making. It reinforces that every decision when backed by strong data has the potential to strengthen the organization in accordance with more precise goals.

Figure 7. Result of Analytical Findings for Optimal Decision Outcomes

During the exploration and also in-depth analysis of the data owned by the author found many insights that contained new understandings and breakthroughs, which served as a potential in revolutionizing the framework for decision making that already existed in the company. The findings that exist and are described as a whole in the figure above not only contain information but provide a narrative that reflects on the reality that occurs in the operational process and provides potential opportunities in the purchase order process carried out by ACA Company. By processing complex datasets into a comprehensive visualization, the author can provide a clearer picture for stakeholders to capture the narrative and story of the data. This provides decision makers with information that supports them to make decisions not only based on intuition but supported by empirical evidence. For example, understanding patterns in cancellations can provide insight into inefficiencies and solve problems at the same time. Similarly, by identifying which regions or sites dominate the most, decision makers can provide strategies for specific local challenges [27]. In general, the author's analysis acts as a compass that can guide through a wealth of data leading to informative and impactful decisions. By getting data driven insights into the decision making framework, the company not only reacts but can anticipate the existing problems so that the business is maintained and decisions become the potential to move in a positive direction.

Business Solution

In today's fast-paced business environment, real-time insights are not just a luxury but a necessity. A Real-time Monitoring Dashboard stands at the confluence of data analytics and operational agility, offering organizations an immediate view of their key performance indicators [28]. Such dashboards transform raw data into visual, actionable insights, allowing stakeholders to make informed decisions promptly. By bridging the gap between data collection and data interpretation, real-time dashboards empower businesses to proactively address challenges, harness opportunities, and maintain a competitive edge in a constantly evolving marketplace.

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Purpose

A real-time dashboard serves as a central point of reference, offering insights at a glance. It converts raw data into actionable information, helping stakeholders make informed decisions. Real-time data visualization ensures that stakeholders don't have to wait for weekly or monthly reports to identify and address issues. Immediate data access can expedite decision-making processes.

Dashboard Creation

As mentioned above regarding the purpose of the dashboard, which is to make important information for stakeholders, the author starts making dashboards by going through several steps, including:

1. Introduction

In this process, the author coordinates with the ACA Company in preparing a dashboard to create a model that can help as an initial form. The author and the party concerned agree that the objective of this dashboard is to track cancellations, performance and also the reasons that can cause cancellation.

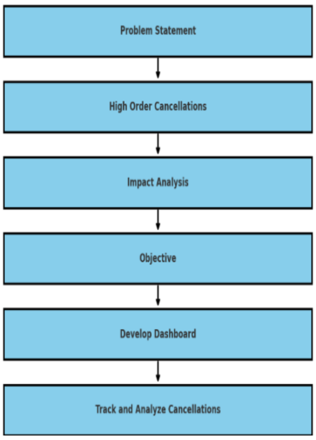

Figure 8. Dashboard Creation Workflow Diagram
Source: Author's Analysis

2. Background

Making dashboards can be done after knowing the planning and also knowing the existing architecture in the company's internal. Before starting the dashboard creation, the author observes the existing system at ACA Company so that the dashboard creation can take place efficiently without doing repetitive activities. In the picture below, it explains the current system that occurs when tracking.

Figure 9. Old System on Accessing Information Related to Order Cancellation
Source: Author's Analysis

By knowing the process above, it is clear that the decision maker can only see the cancellation process in a monthly period, which should be able to intervene if a cancellation

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occurs.

3. Development

Research Phase

In this phase, the author communicates with stakeholders at ACA Company, especially those who often operate regarding purchase orders in learning maximum goals for the dashboard creation process. After knowing the architecture owned by ACA Company, the author makes a diagram of the data movement process that can be used in the dashboard.

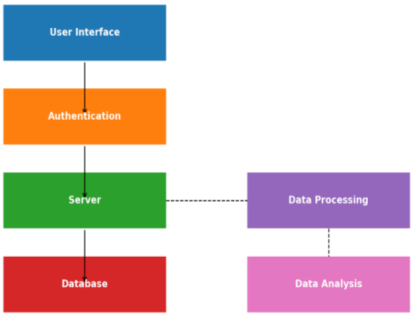

Figure 10. Data Information Workflow
Source: Author's Analysis

The process above explains the process that will be implemented in the form of a dashboard. This framework is general due to the absence of tools owned by ACA Company in realizing the visualization process. So, as a form of offer from the author, the author makes this framework general in the hope that in the future when ACA Company invests in data analytics, it can work with any tools based on this framework. The process starts with the dashboard user interface on the tools, this starts with checking the access that the user has due to resource limitations for several data departments so that data security can be maintained properly. Authentication in the form of a validation process that the user does or does not have access to this dashboard.

The process continues to the server to find out what list is needed to provide information for the dashboard. In this case, the data is about purchase orders and more specifically about Order Cancellation. After knowing what is needed, then proceed to the database for storing what has been done. On the access server, an analyst can perform an analysis process or create a feature, one of which is a dashboard or data analysis with any form of tools such as Python, SQL or visualization tools such as Tableau. In this process, the author uses Tableau as a tool in making dashboards and Python as a form of brainstorming in the initial process of data owned by ACA Company.

Design Phase

After making a diagram in the access to information or data flow used, the author makes a layout so that the dashboard can be accessed neatly and can be conveyed optimally when the user needs a related dashboard.

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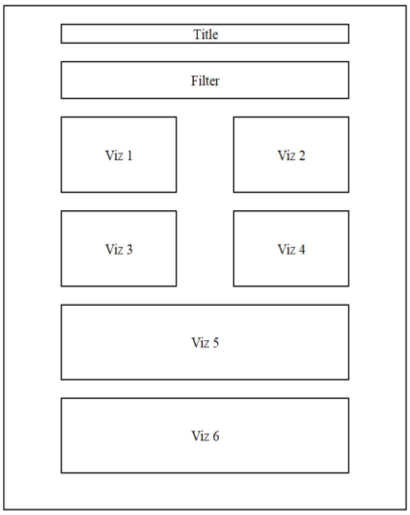

Figure 11. Dashboard Layout
Source: Author's Analysis

4. Feature and Dashboard Component

The subsection below will explain the components and features that will be implemented on the dashboard for Order Cancellation that occurs at ACA Company.

Date and Region Filter

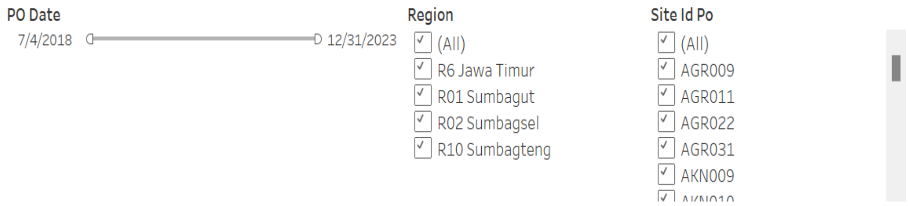

Figure 12. Date and Region Filter
Source: Author's Analysis

The interface on the Order Cancellation dashboard starts with filters on the PO date, Region and Site listed on the project. This feature allows the user to focus on a subset of the analysis. For region and Site ID, it can give the user the freedom to know the analysis in geographic level.

Top 10 Issues Leading to Cancellations

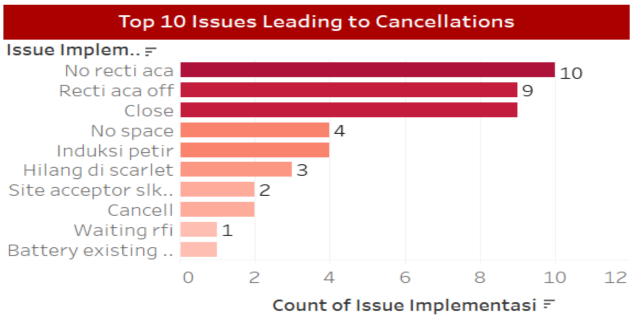

Figure 13. Most Frequent Issues Bar Chart
Source: Author's Analysis

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Central to this dashboard is the use of a visualization to show issues that often occur in Order Cancellations. This visualization is formed in ranking and bar charts so that users can see quickly that what issues often occur and can provide mitigation in a responsive manner.

Distributions of Potential Lost Value from Order Cancellations

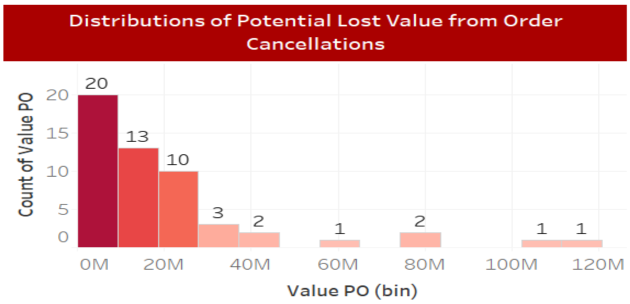

Figure 14. Financial Impact Visualization on Order Cancellations
Source: Author's Analysis

The distribution that occurs in potential lost value describes the potential financial lost value that occurs due to order cancellations. Visualization or bar charts are depicted in value-based segmentation based on high impact to low impact cancellations. This can help in prioritizing issues.

Number of Cancelled Order per Region

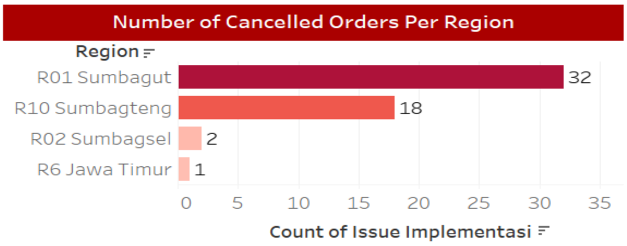

Figure 15. Number of Cancelled Orders Per Region Bar Chart
Source: Author's Analysis

Below the aforementioned charts, a bar graph details the number of cancelled orders categorized by region. By knowing the higher implication that occurs in the region affected by order cancellation, it can be reported to the operational team as a form of improvement.

Total Potential Lost Value per Region

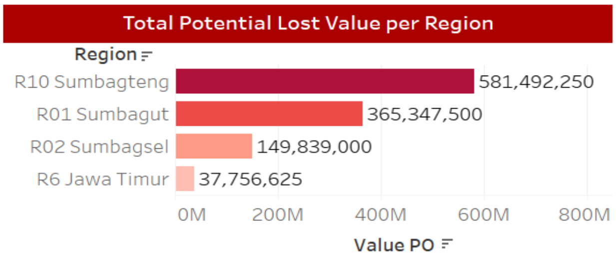

Figure 16. Total Potential Lost Value per Region
Source: Author's Analysis

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Unlike the previous bar chart, this visualization illustrates the potential lost value in the regional section. By calculating the potential lost value in order cancellations, stakeholders can measure the economic significance and resource allocation of a region.

Comparison of Count and Total Potential Lost Value

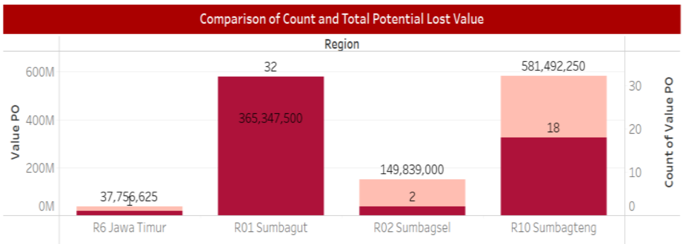

Figure 17. Hollistic view of Count and Total Potential Lost Value
Source: Author's Analysis

This dual-axis chart serves as a comparative analysis tool, juxtaposing the count of cancellations against the potential financial loss. The side-by-side visual representation allows for an immediate correlation analysis between the frequency of cancellations and their respective financial implications.

The use of data analytics at a fast rate can help companies make decisions (Alshboul, 2015). Despite the large amount of data and the high level of diversity with big data analytics, a process can be carried out to reveal patterns that can ultimately help employees in carrying out their duties. Data analytics is very important because as a tool it can be very useful in maximizing resources and also helping companies in determining strategies at the corporate level so that they can predict what should be the basis for decision making [10].

Based on a report published by Mckinsey, there is an increase of 5-6% in the context of productivity for leveraging data analytics in companies that have not implemented the concept of data analytics [11]. Big data can help address critical challenges of predictive analytics that refer to data capture, storage, transfer & sharing [12].

For example, analytics can help companies to enhance supply chain processes and ultimately the performance of the company [12]. Monitoring data, comparing the company's performance to the market trend, and analyzing the transaction of company's projects also the benefits of Big Data Analytics on supply chain management.

CONCLUSION

A data-driven decision-making culture, ACA Company can enhance its purchase order management. The analysis reveals that data analytics enables stakeholders to strategically address order cancellations by identifying regions with higher potential for cancellations and prioritizing interventions based on common cancellation reasons. Moreover, the financial impact of cancellations is better understood by considering both their frequency and associated values. The prioritization of high-value cancellations allows for effective decision-making to mitigate potential revenue loss. Additionally, the integration of data analytics into purchase order management processes introduces a real-time dashboard, transforming raw data into actionable information. This not only facilitates quick decision-making but also serves as a catalyst for organizational change, fostering a culture that values and utilizes data-driven insights to optimize the overall management of purchase orders at ACA Company.

REFERENCES

[1] N. Richsandiant, Sunanto, and K. R. Sari, "Pengambilan Keputusan atas Pesanan Khusus Berdasarkan Perhitungan Biaya Relevan," *J. Ekon. Bisnis, Akunt. dan Sist. Inform.*, vol. 1, no. 1, pp. 1–9, 2021.
[2] N. S. S. Sugiana and B. Musty, "Analisis Data Sistem Informasi Monitoring Marketing; Tools Pengambilan Keputusan Strategic," *Jutisi J. Ilm. Tek. Inform. dan Sist. Inf.*, vol. 12, no. 2, pp. 696–708, 2023.
[3] I. D. Febriani, I. A. Pangestu, S. Gee, L. P. Hulu, and A. Wijoyo, "Sistem Informasi Manajemen dalam Menunjang Pengambilan Keputusan," *JRIIN J. Ris. Inform. dan Inov.*, vol. 1, no. 2, pp. 473–482, 2023.
[4] P. F. Johnson, M. R. Leenders, and A. E. Flynn, "Purchasing and supply management," *McGraw-Hill*, 2015.
[5] S. Hasan, "Purchase management system," *ResearchGate*, 2016.
[6] A. E. R. Kesatriawan, J. M. Meliska, M. Indriani, and T. T. Putera, "Kedudukan purchase order sebagai dasar kewajiban pembayaran," *Notaire*, vol. 5, no. 2, pp. 179–196, 2022, doi: https://doi.org/10.20473/ntr.v5i2.35000.
[7] K. Lysons and B. Farrington, "Procurement and supply chain management," *Pearson UK*, 2020.
[8] R. Ahmed, S. Saheen, and S. P. Philbin, "The Role of Big Data Analytics and Decision-Making in Achieving Project Success," *J. Eng. Tchnology Manag.*, vol. 65, p. 101697, 2022.
[9] I. Rahimi, A. H. Gandomi, S. J. Fong, and M. A. Ülkü, "Big data analytics in supply chain management: Theory and applications," *CRC Press.*, 2020.
[10] P. M. Giannakos, I. O. P., and J. K., "Information Systems and e-Business Management," *Inf. Syst. E-bus. Manag.*, vol. 16, no. 3, pp. 547–578, 2018.
[11] J. Bughin, "Big data, Big bang?," *J. Big Data*, vol. 3, no. 1, pp. 1–14, 2016, doi: https://doi.org/10.1186/s40537-015-0014-3.
[12] A. Gunasekaran *et al.*, "Big data and predictive analytics for supply chain and organizational performance.," *J. Bus. Res. 70, 308–317.*, vol. 70, pp. 308–317, 2017, doi: https://doi.org/10.1016/j.jbusres.2016.08.004.
[13] H. . Al-Tarawneh, "The main factors beyond decision making," *J. Manag. Res.*, vol. 4, no. 1, 2011, doi: https://doi.org/10.5296/jmr.v4i1.1184.
[14] K. Paunović, "Data processing and storage. In Encyclopedia of Public Health," *Springer Netherlands.*, pp. 210–213, 2008, doi: http://dx.doi.org/10.1007/978-1-4020-5614-7_691.
[15] F. Huang, "Data processing. In Encyclopedia of Big Data," *Springer Int. Publ.*, pp. 1–4, 2019, doi: http://dx.doi.org/10.1007/978-3-319-32001-4_314-1.

Jurnal Ekonomi
Volume 13, Number 02, 2024, DOI 10.54209/ekonomi.v13i02
ESSN 2721-9879 (Online)
https://ejournal.seaninstitute.or.id/index.php/Ekonomi

[16] M. Pohl, D. G. Staegemann, and K. Turowski, "The performance benefit of data analytics applications," *Procedia Comput. Sci.*, vol. 201, pp. 679–683, 2022, doi: https://doi.org/10.1016/j.procs.2022.03.090.
[17] M. Q. Shabbir and S. B. W. Gardezi, "Application of big data analytics and organizational performance: The mediating role of knowledge management practices.," *J. Big Data*, vol. 7, no. 1, 2020, doi: https://doi.org/10.1186/s40537-020-00317-6.
[18] M. J. Sousa, A. M. Pesqueira, C. Lemos, M. Sousa, and Á. Rocha, "Decision-Making based on Big Data Analytics for People Management in Healthcare Organizations," *J. Med. Syst.*, vol. 43, no. 9, 2019, doi: https://doi.org/10.1007/s10916-019-1419-x.
[19] O. D. Apuke, "Quantitative research methods : A synopsis approach," *Kuwait Chapter Arab. J. Bus. Manag. Rev.*, vol. 6, no. 11, pp. 40–47, 2017, doi: https://doi.org/10.12816/0040336.
[20] I. Lenaini, "Teknik Pengambilan Sampel Purposive dan Snowball Sampling," *Hist. J. Kajian, Penelit. Pengemb. Pendidik. Sej.*, vol. 6, no. 1, pp. 33–39, 2021.
[21] AroraMeharban, "Advantages of Python programming language in the world of big data: Poster poster abstract," *J. Comput. Sci. Coll.*, vol. 37, no. 3, 2021.
[22] A. Subasi, "Practical machine learning for data analysis using python," *Acad. Press*, 2020.
[23] K. Sahoo, A. K. Samal, J. Pramanik, and S. K. Pani, "Exploratory Data Analysis using Python," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 12, pp. 4727–475, 2019, doi: https://doi.org/10.35940/ijitee.l3591.1081219.
[24] J. Brownlee, "Data preparation for machine learning: Data cleaning, feature selection, and data transforms in Python," *Mach. Learn. Mastery*, 2020.
[25] M. Kösters, "The five benefits of data visualization," *Deloitte Netherlands*, 2022. https://www2.deloitte.com/nl/nl/pages/tax/articles/bps-the-five-benefits-of-data-visualization.html
[26] Q. Li, "Overview of data visualization In Embodying Data," *Springer Singapore*, pp. 17–47, 2020, doi: http://dx.doi.org/10.1007/978-981-15-5069-0_2.
[27] I. Kopanakis, K. Vassakis, and G. Mastorakis, "Big data in data-driven innovation: The impact in enterprises' performance.," *ResearchGate*, 2016.
[28] I. H. Sarker, "Data science and analytics: An overview from data-driven smart computing, decision-making and applications perspective.," *SN Comput. Sci.*, vol. 2, no. 5, 2021, doi: https://doi.org/10.1007/s42979-021-00765-8.