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USING SAP ANALYTICS CLOUD (SAC) FOR VISUALIZING DATA AND DETECTING PROBLEMS

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ABSTRACT

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The way of data organization will affect directly business decision-making. The traditional performance of data in rows and columns is poor and limited. However, data is crucial evidence to tell organizations what is happening with their business. Therefore, arranging and displaying readable data is necessary. And data visualization is dominant to improve data performance. SAP Analytics Cloud (SAC) is a leading solution for visualizing data and making decisions. In addition, this software also offers predictive analytics and business planning functions. The purpose of this thesis was to bring a better understanding of how SAP Analytics Cloud works through observing a case company that used SAP Analytics Cloud for visualizing data and detecting problems while they ventured into the US market.

Qualitative case study was a research tool for this report. The applied SAP Analytics Cloud process of the case company was described. It started by evaluating data, preparing data, visualizing and analysing data, and ended by presenting the results of the findings. Moreover, the suggestions for minimizing the adverse impact on the issues were included.

Based on features embedded in SAP Analytics Cloud, Fond Rouge exposed counterfeit and inferior issues that were happening in several cities of the US. These problems were affected straight to their revenue in this market. Thanks to these findings, Fond Rouge had a comprehensive overview to figure out the best way to narrow down negative effects.

Although the scope of this study only analysed data visualization and predictive analytics functionality of SAP Analytics Cloud through the case company, this software is truly outstanding. With using artificial intelligence (AI), machine learning, and automate predictive analysis, it provides businesses smart insights with least manual intervention. Furthermore, it also improves the way of data performance, enhances decision-making, and supports the business management.

Key words

Business intelligence, data analytics, data integration, data modelling, data performance, data preparation, data visualization, problem detection, SAP Analytics Cloud (SAC)

CONCEPT DEFINITIONS

List of Abbreviations

AI	Artificial Intelligence
BI	Business Intelligence
CORS	Cross-Origin Resource Sharing
CSV	Comma-Separated Values
DSS	Decision Support System
ERP	Enterprise Resource Planning
IaaS	Infrastructure as a Service
JDBC	Java Database Connectivity
OLAP	Online Analytical Processing
PaaS	Platform as a Service
SaaS	Software as a Service
SAC	SAP Analytics Cloud
SAP BPC	SAP Business Planning and Consolidation
SAP BW	SAP Business Warehouse
SAP IBP	SAP Supply Chain Planning Solution
XLSX	Microsoft Excel Spreadsheet Extension

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1 INTRODUCTION

Nowadays, the big data concept is familiar to organizations, from profit to non-profit, even governments. The generated data is unlimited; simultaneously, it is also non-stop to be gathered wherever and whenever through member cards, surveys, cookies, social media, cameras, payment systems, sensors, smartphones, and so on. As a result, the volume of data has grown exponentially. The core of the matter here is how a company can utilize the data to expand and consolidate its competitive advantages. In addition, the changes and increased complexity in the business landscape and advances in hardware and development of cloud technologies lead to finding out which sophisticated software can provide businesses smart insights with the least manual intervention and adapt to these technologies, which plays a crucial task for organizations.

Moreover, globalization is speeding up and becoming a key driver today, especially in the digital realm. Therefore, organizations launch the penetration strategy to expand their businesses outside nations and gain larger shares. However, companies can raise problems when they enter new markets, such as predicting wrong customer insights, not understanding the local culture, counterfeited products, or controlling quality discrepancy issues. The time and approach of organizations identifying these confronted problems continue to highlight the importance of choosing the right software in the daily operation of businesses. The quicker the matters are exposed, the more adverse impacts to the company are reduced significantly.

SAP Analytics Cloud (SAC) is an outstanding software and solution for organizations that want to utilize the development of business intelligence (BI), augmented and predictive analytics, and planning capabilities in one cloud environment. Furthermore, the combination of artificial intelligence (AI), machine learning, and automated predictive analysis makes SAC take the leading position. There is a background for this study.

The research method used in this report is qualitative - case study research. The amount of data in a case company is massive. The process of using SAC to visualize data and detect problems of the case company will follow these steps. Starting with data types should be gathered correctly, and next is data wrangling before moving to develop models and calculate relevant measures in SAP Analytics Cloud (SAC). Then, based on the built models, analysing data is the coming step, and finally, the results and suggestions are presented. The mentioned process can answer three research questions: How can SAC

support the case company to detect the facing problem? How does SAC benefit the case company's data performance and data analysis? How does SAC improve the case company's decision-making?

By going through these three research questions, the highlighted features of the SAP Analytics Cloud (SAC) software were explored. In addition, the new ways of data performance, which help organizations get an overview and expose problems quicker, are also presented in this study.

Moreover, through observing the case company applying the SAP Analytics Cloud to help them detect the issues in their new market process, the aim of the study is to present the benefits of using the SAC software in an organization's daily operations, such as visualization, prediction, analytics to find out the patterns, phenomenon, or strange behaviours, and so on. Also, how SAP Analytics Cloud can improve data-driven decision-making and support business management will be introduced.

However, the study has its limitations. The scope of this study only presents the data visualization and predictive analytics functions of SAP Analytics Cloud (SAC). The other functions, such as the planning capabilities into one cloud environment and advanced analytics enterprise-wide, are not included in this study. Moreover, the data used in this study is statistic, not dynamic data. Therefore, we do not have a chance to discover the updated data in real-time option. In addition, a data source used in the case company is an XLS file, which leads to restricting the examination with other supported data sources such as Microsoft (MS) Azure, Amazon Web Service, and Google Cloud Platform.

2 INTRODUCTION OF SAP ANALYTICS CLOUD

Today, data is a critical corporate asset of every organization. However, the idea of data in the schools' programs is usually described as "raw" data, which means the worthless collection of text, symbols, and numbers; therefore, data must be processed or put in given contexts before having meaning. With the development of smart devices and social media, data is also gathered from videos, audio, and pictures. Data has to be interpreted to become information; in other words, information is the output of the data interpretation process. (Cambridge Assessment International Education 2017.) Then, organizations can make decisions or give forecasts based on this information.

According to Watson (2013), analytics is understood as the "rocket science" algorithm in neural networks and machine learning. In the business world, the methods used to discover helpful patterns within data or to optimize efficiency are also referred to as analytics. In detail, descriptive analytics and predictive analytics are two types of analytics. While reporting, OLAP, dashboards/scorecards, and data visualization are considered descriptive analytics that analyse "what has occurred", predictive analytics focuses on predicting "what will occur" to serve for maximizing performance.

It is not natural when analytics becomes a common concern and attracts numerous articles, books, research, and surveys. In the big data era, leaders want to know which information they hold is valuable and worthwhile. Moreover, they are also concerned with how companies can utilize data to grow and enhance their performance, such as making accurate decisions or giving better forecasts. Therefore, analytics-driven business models are emerging. However, poor analytics can ruin the potential value of high-quality data; conversely, good analytics can extract insights from even second-rate data (McKinsey Global Institute 2016). Three core benefits of analytics are to generate valuable insights, improve core business operations, and communicate the benefits of using data to increase the use of analytics (SAS Institute Inc. 2019).

In addition, data and analytics can assist an organization in defining teams, resources, and workflows in the area of the innovation process. Also, it can be utilized to form new hypotheses by uncovering new patterns that managers have not recognized before. Furthermore, data and analytics can transform research for developing new products in various fields. Then again, there is no denying that data and analytics can be used to enhance the online user experience. Meanwhile, human limitation and biases can be overcome by getting helps from analytics to improve the decision-making process more quickly, accurately, consistently, reliably, and transparently. (McKinsey Global Institute 2016.)

Cloud computing is a model that provides users with access rights to a shared pool of configurable computing resources such as networks, servers, storage, applications, and services. The purpose of this technology is to offer rapidly and released with minimal administration effort or service provider interaction. Five characteristics of cloud computing include on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service. While cloud computing service is provided in three ways - software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS), four models are deployed - private cloud, community cloud, public cloud, and hybrid cloud. (Mell & Grance 2011.)

Above is the background of SAC that pointed out the necessity of interpreting data into information. What are analytics and benefits of it? Moreover, the definition of cloud computing technologies, three service models, and four deployment models are also introduced.

2.1 Definition

According to Datar (2019), SAC is a SaaS solution based on the SAP Cloud Platform. This software contains planning, business intelligence, and predictive analytics functionalities in a single cloud-based solution. It concentrates on user-centric and allows users can handle data exploration, planning, predictive analytics, and data visualization tasks in a one-stop-shop solution.

Additionally, SAP Analytics Cloud is a next-generation cloud-based application. This application is built into the SAP Cloud Platform and supports organizations in exploring data, visualizing and analysing data, generating financial plans and forecasting. Importantly, all functionalities are in one product. It includes business intelligence, planning, predictive analytics, governance, and risk management to meet the businesses' analytic requirements. (Ahmed 2017.)

Ahmed (2017) also raised that although SAC is built in the SAP Cloud Platform, SAC works well with both SAP and non-SAP sources, consisting of Google Drive, Salesforce, Concur, SQL server, and CSV files. Moreover, SAC enables organizations to generate connections to these clouds and on-premise data sources – SAP HANA, SAP BW, and S/4 HANA sources safely and securely.

2.2 History and Innovation

In recent years, since the business landscapes have significant changes and become more complicated, businesses would like to use social media data, mobile device data, and big data to satisfy higher customer expectations. It leads to the business software used to process the volume of digital information growing exponentially. In a fast-paced, fluid, and dynamic environment, business software has to be improved continuously to adapt to the changing situation. (Adivar 2021.)

According to Sidiq (2022), the world of analytics has massive changes. The increased usage of analytics solutions inside business units, the transformation from on-premise to cloud-based vendors, and the growing volume of data are the background to impose new challenges for analytics solutions and their suppliers. Under these challenges, many businesses are struggling to remain competitive. Therefore, uncomplicated and intuitive solutions are sought by business units when they want greater freedom in analysing data. In addition, graphical reporting is preferred to tabular form. SAC was released to address this demand. It is positioned as a flexible analytics platform with numerous choices for creating self-service scenarios.

2.2.1 History

In the early 2000s, SAP has been a player in the business intelligence (BI) space with many in-house products such as SAP Lumira, SAP Predictive Analytics, and SAP Business Planning and Consolidation. These solutions are implemented on-premise. SAP Cloud for Analytics was released simultaneously with the new SAP S/4 HANA in 2015. Then, it was renamed twice with SAP BusinessObjects Cloud in 2016 and SAP Analytics Cloud in 2017. (Rheinwerk Publishing 2022.)

Sidiq (2022) mentioned the data value formula in picture 1. This formula determines the value of an organization's data based on its components, including volume, quality, and usage. Essentially, the highest values can be obtained from the data if the data has a considerable volume, high quality, and correct usage. SAC is developed to cover the usage portion of this formula.

The needed insights are derived from choosing the correct data types. Moreover, SAC benefits from SAP's heavy investment in developing a modern and last-long analytics platform based on cuttingedge technology and the extensive expertise of SAP in the industry. It is designed as functionalities and services centred on all the core areas of business analytics. While investing entirely in cloud-based or on-premise solutions, SAP is also working hard to make hybrid scenarios realistic. Therefore, the seamless integration between cloud-based and on-premise is the primary goal of SAP to provide their users with the best of both worlds. (Sidiq 2022.)



PICTURE 1. Data Value Formula (Sidiq 2022)

2.2.2 Innovation

Like SAP S/4 HANA, simplification is the most advantageous between SAP Analytics Cloud (SAC) and its predecessors. In the previous analytics, the users had to switch between various solutions to accomplish data visualization, reporting, predictive analytics, and other business intelligence (BI) functions. By contrast, SAP Analytics Cloud allows its users to complete these tasks in a single solution. (Rheinwerk Publishing 2022.)

SAP Analytics Cloud helps to optimize individual processes in a variety of ways. Firstly, data processing is faster with a live connection to an SAP S/4 HANA database than with analysts who work with traditional databases. Secondly, SAP Fiori got its inspiration from five core design guidelines based on user experience instead of the user interface. It supports users to navigate easily through the solutions. Finally, the self-service approach is one of the powerful functionalities of SAP Analytics Cloud. It improves the making of better business decisions by offering the ability to create reports and perform data analysis in faster and simpler ways. (Rheinwerk Publishing 2022.)

In addition, the newest component of SAP Analytics Cloud – analytics designer – was released in the second quarter of 2019. This component offers a tool for power users to create complicated analytical applications. By utilizing scripting and defining more detailed settings on a chart, behaviour, filters, and other features, the analytics designer allows users to extend standard reports. Moreover, the analytics designer differs from the self-service approach compared to storytelling and business intelligence

(BI). This tool is designed for individualized and highly customized dashboard purposes to serve business divisions and users. Business users do not require to acquire deep knowledge and coding skill. They consume the dashboards, customize and build for specific use cases. (Sidiq 2022.)

2.3 Core SAP Analytics Cloud Functionalities

SAP Analytics Cloud is a new generation of Software as a Service (SaaS). It is developed on the SAP HANA Cloud that offers Business Intelligence, Predictive Planning, Augmented Analytics, and Analytics Designer for users in a one-stop-shop solution to cope with analytical needs. These four functionalities make SAP Analytics Cloud dominate in the peer groups of Power BI solutions. (Rheinwerk Publishing 2022.) Picture 2 gives the core and analytics capabilities of SAP Analytics Cloud.



PICTURE 2. The core and analytic capabilities of SAP Analytics Cloud (Rheinwerk Publishing 2022)

2.3.1 Business Intelligence

Business Intelligence (BI) is a data-driven decision support system (DSS) used for gathering, storing, and analysing data to deliver information to planners and decision-makers to improve the timeliness and the quality of the provided information to the decision-making process. The concentration of business intelligence is on analysing vast amounts of data regarding a company and its operations. Altogether, business intelligence systems are understood as the systems that deliver actionable information and knowledge at the right time, in the right place, and the right form. (Negash & Gray 2008.)

Sidiq (2022) stated that the Business Intelligence (BI) area is a critically important part of SAP Analytics Cloud. It contains the widely used scenario of visually analysing data. Ensuring users can have a unified and homogeneous experience across the product, a story allows users to go through all workflows in the business intelligence area, planning, and some intelligent support functions.

According to Rheinwerk Publishing (2022), data connectivity, data modelling, storytelling and reporting, collaboration, and data quality are available in the business intelligence area of SAP Analytics Cloud. The users, who execute the business intelligence to improve the decision-making process, will mainly focus on data collection (gathering data and entering data into the system), data visualization (generating helpful reports with the collected data), and publication (releasing the created reports).

2.3.2 Predictive Planning

For navigating the development of businesses, the forecast should be as precise as possible. It is a difficult task, even can be an impossible mission. As a result, planning plays a pivotal role in any business and organization. However, due to the complexity of this topic, planning is frequently regarded as a science. The planner has responsibilities to ensure budgets and goals are met while long-term strategies are maintained properly and preferably. (Sidiq 2022.)

The planning engine is the second component of SAP Analytics Cloud. It provides numerous tools and full-fledged planning components to establish planning processes and track their implementation, which support a tabular planning process with visual and intuitive functionalities. (Sidiq 2022.) The tools in the planning section focus on end-to-end business planning processes, such as data model extension, formula application, and free chart generation (Rheinwerk Publishing 2022).

In SAP Analytics Cloud, predictive planning refers to the ability to perform time series forecasting scenarios directly on top of planning-enabled models to provide a solid baseline for forecasting activities (Chabert 2021).

2.3.3 Predictive Analytics

Eckerson (2007) described predictive analytics as a set of business intelligence (BI) technologies that may be used to forecast behaviour events by exposing the relationships and patterns which come from vast amounts of data. Predictive analytics is differentiated from others that primarily focus on analysing historical data instead of concentrating on forward-looking, predicting the future based on previous events.

Predictive analytics forms a general principle from a specific set of facts or ideas, called inductive. No assumptions about the data are given; instead, predictive analytics allows data to lead the way. Statistics, machine learning, neural computing, robotics, computational mathematics, and artificial intelligence are some techniques to be exploited in predictive analytics. Instead of narrowing down to a subset, predictive analytics discovers meaningful relationships and patterns from large volumes of data. (Eckerson 2007.) Picture 3 illustrates the spectrum of business intelligence technologies.

Additionally, Sidiq (2022) stated that the predictive analytics component is embedded in SAP Analytics Cloud. Its noticeable features include smart assist and smart predict to facilitate users in performing various analysis types.



The Spectrum of BI Technologies

PICTURE 3. The spectrum of business intelligence technologies (Eckerson 2007)

2.3.4 Analytics Designer

Before diving deeper to understand the analytics designer, the concept of the story and analytics application should be defined. In SAP Analytics Cloud, a story is where users tell their story about their organization by combining data and visualization to uncover hidden insights within their data (SAP Community, page "Stories, Reporting, and Data Exploration", paragraph "Stories"). Reporting and interactivity are the two main concentrations of a story. It offers a wide range of tools to help users generate visualization and interactive controls for viewers. Furthermore, the story can be employed flexibly as well as applied highly in many complex use cases. (Sidiq 2022.)

Specifically, a creator goes through most of the process with guidance from the story environment. Dialogue boxes and automatic functionalities are exploited to help the storyteller easily add input controls or filters to a story. (Sidiq 2022.) Also, the development time of a story is a few hours or a few days (Laj 2020). However, in the story design-time environment, the level of customization is limited to the foreseen possibilities (SAP SE 2022).

Meanwhile, an analytics application offers the creator a higher-level degree of freedom with a less guided approach. Based on a development environment, the analytics designer can use numerous tools and functionalities to create a complicated dashboard. (Sidiq 2022.) According to SAP SE (2022), an analytic application displays data in multiple formats allowing the developer to navigate and plan. Also, the analytics application provides a wide range stretching from simple static dashboards with static information to highly customizable applications.

Generally, compared to story functionality, the analytics application is more flexible to customize. However, as Laj (2020) stated that the analytics application requires higher skill levels to generate. And the development time is from a few days to a few weeks.

In short, story and analytics applications are related to each other. They share widgets and functionalities to a vast expansion; however, because of scripting, some widgets and custom logic capabilities are only deployed in analytics applications. (SAP SE 2022.)

SAP SE (2022) explained that Analytics Designer is the functionality in SAP Analytics Cloud. It is developed based on core story components to keep them synchronized as users progress and allows users to create analytics applications by creating a dedicated design environment. It does not specify the UX or UI design aspect. Conversely, it only focuses on creating an analytics application process involving defining the data model, laying out the screen, configuring widgets, and connecting everything using custom scripts.

2.4 Data Integration and Data Modelling in SAP Analytics Cloud

Live data is required to get full benefits from analytics. If an organization wants to establish successful business analytics applications, a vital task is to integrate the fully and correctly the data. (Sidiq 2022.) Therefore, seeking better solutions for data integration is a common concern of every business; however, it is challenging to solve with large-scale data integration projects that involve a variety of data silos that contains crucial data (Allen 2022). Thus, SAP Analytics Cloud comes with various integration options with both existing landscape and a standalone platform can be integrated (Sidiq 2022).

After getting successful data integration, the basis of effective analytics is a specified data model (Sidiq 2022). A well-defined data model is to remove redundancy, lowers storage needs, and facilitates effective retrieval. Not only that, a thorough and optimal data model provides all systems with a "single source of truth" that is crucial for efficient operations and compliance with regulations and regulatory requirements. (SAP Insight, chapter "What is data modelling?", paragraph "Why is data modelling important?".) Therefore, SAP Analytics Cloud offers a variety of solutions for data modelling (G 2019).

2.4.1 Data Integration in SAP Analytics Cloud

Lenzerini (2002) described data integration as merging data from various sources and presenting it to the users in a cohesive view. Simultaneously, data integration allows business users to view the business performance in a real-time. Data integration is the first step to reforming data into valuable and meaningful information. By pursuing data integration as a strategic function, any organization can draw support from advanced analytics processes or build multi-dimensional views of customers (Sayiram 2021).

Data integration in real-time is beneficial to organizations in many aspects. At first, accessing real-time data allows a business to be proactive before opportunities or potential bottlenecks happen. The organization's decision-making capabilities also reap benefits from it. Next, by approaching real-time customer data and historical data, the business can reach out to its customers with active support at the right time. Through it, the enterprise can enhance both the customer experience and revenues. Then, accessing real-time data can help the organization simplify their operations and reap benefits from that simplification, such as improving processes, reducing costs, and increasing production across various business departments. Finally, by accessing historical data and real-time data, the business can forecast customer needs and demands more precisely and quickly. (Sayiram 2021.)

SAP Analytics Cloud supports all data sources integration from live connections and import connections. A live connection is also known as a remote or online connection. (Sidiq 2022.) Data is "live" in this connection. It allows a user opens a story in SAP Analytics Cloud, and the source system will reflect immediately once data changes. (Neelam 2021.) The cloud does not receive any data transferred from the data warehouse (Capgemini 2020). Instead, the story only contains metadata. Metadata is designed to store non-sensitive data but is required to generate charts or various forms of visualization (Sidiq 2022). The queries are executed directly in the back end, and any outputs are generated based on the results of these queries (Radulescu 2019). In particular, live data integration includes two scenarios: connections via Cross-Origin Resource Sharing (CORS) and connections via Tunnels (Sidiq 2022).

In the live integration, SAP Analytics Cloud can connect to eleven types of live data sources. There are SAP HANA, SAP Business Warehouse (SAP BW), SAP BW/4HANA, SAP S/4HANA, SAP Business Dijects universes, embedded SAP Business Planning and Consolidation (embedded SAP BPC), SAP S/4HANA Cloud, SAP Business Technology Platform (SAP BTP), SAP Data Warehouse Cloud, SAP HANA Cloud, and SAP HANA Cloud. However, in the live data connections option, every data source has its own prerequisites and minimum revisions. (Sidiq 2022.)

The advantages of using a live connection are: firstly, there is no data replication, and the live integration can avoid data transfers from the source system. Secondly, the latest data is automatically updated, which means the data is real-time data. Thirdly, SAP Analytics Cloud allows users to develop complicated models and calculations in source systems. Finally, sensitive information will be kept in an organization's internal network, protected by a firewall. (Radulescu 2019.) An import connection is called data import, data acquisition, or local data (Sidiq 2022). Data acquisition is to replicate data sources from on-premise or cloud into SAC (Peruzzi 2021). According to Pierre (2021), replicated data is in SAP Analytics Cloud in-memory HANA Database. And then, the model and data are stored in this software. Although data import implies data replication, the data is encrypted and fully protected. However, this type of integration has volume limitations such as file size limits; row, column, and cell limits.

Picture 4 shows that SAP Analytics Cloud Connector and SAP Analytics Cloud Agent are components required for import integration. And SAP Analytics Cloud supports the data sources from file upload (CSV and Microsoft Excel files), SAP BW and SAP BW/4HANA, SAP HANA, SAP Cloud for Customer, SAP S/4HANA and SAP S/4HANA Cloud, SAP ERP, SAP BPC (versions for SAP NetWeaver, for Microsoft, and SAP BW/4HANA), SAP BusinessObjects universes, SAP Integrated Business Planning for Supply Chain (SAP IBP), SAP SuccessFactors and SAP SuccessFactors Workforce Analytics, SAP Business ByDesign, SAP Concur, SAP Fieldglass, Google Drive, Google Sheets, and Good BigQuery, Salesforce, Open Connectors of the SAP Integration Suite, Java Database Connectivity (JDBC) driver for additional data sources, OData services, Partner connector offered by APOS, CDATA, and DataDirect Cloud. (Sidiq 2022.)



PICTURE 4. SAP Analytics Cloud Connector and SAP Analytics Cloud Agent (Pierre 2021)

A dominant characteristic of an import connection is SAP Analytics Cloud assists the connecting between SAP and non-SAP data sources with lower version levels required rather than a live connection. In addition, when importing data from an SAP BW to SAP Analytics Cloud, an authorized user can already restrict the uploaded data by applying restrictions or filters. Besides, scheduling is known as one of the specific characteristics of the import connection. The scheduling is planned and executed regularly and enables users automatically update data models in SAP Analytics Cloud. (Sidiq 2022.)

2.4.2 Data Modelling in SAP Analytics Cloud

Data modelling is known as the method of illustrating data flows. It starts with drawing a diagram of how data will enter and exit the database when developing a new or alternative database structure. The flow diagram defines the properties of data formats, data structures, and database handling functions to fulfil the data flow requirements. After creating the database and putting it into use, the data model continues to become the documentation and justification and serves the purpose of the database's existence and the way of designing data flows. (SAP Insight, chapter "What is data modelling?".)

The business intelligence function of SAC includes two crucial components: models and stories (Nguyen 2020). According to SAP Community (2019), a model is an initial step in acquiring insights from Analytics Cloud. This step establishes a connection between the gathered data and the SAP Analytics Cloud software. Stored data sources in an on-premise or cloud can be used for data acquisition or live data to accomplish this connection. Once the data is linked, users can generate a model.

SAC supports different model types to apply to various scenarios (Sidiq 2022). Using data modelling of SAC can help to improve and prepare for analytics. In addition, users modify data in bulk, define categories, build a hierarchical relationship, and customize formulas. (Nguyen 2020.)

In picture 5, data are displayed as rows and columns in SAC. The data's meaningful descriptions and interpretations come from the semantics of a model. Specifically, semantics play a crucial role in deciding whether a column represents a measure or a dimension in data modelling. Furthermore, semantics defines extra components, such as data columns or hierarchical relationships between different columns. (Sidiq 2022.)

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2	T10925	02/26/2016	56.208	Houston	Lijiang	STR10015	29.975601167888	-95.326360908245	Rows Columns Dimensions Measures
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-4	T10666	03/02/2016	114.21	Atianta	Liancheng	STR10002	33.641492940682	-84.445	> Model Requirements No incendenced
5	T10670	03/19/2016	56.1195	Attanta	Liancheng	STR10002	33.641492940682	-84.445	
6	T10683	02/14/2016	106.368	Indianapolis	Llancheng	STR10015	39.719605420296	-86.294159598395 /	 Model Information
.7	T10687	03/14/2016	43.1595	Indianapolis	Liancheng	STR10016	39.719605420296	-86.294159598399	Deta
.8	T10691	03/05/2016	75.8835	Indianapolis	Liancheng	STR10016	39.719605420296	-86.294159598395 +	Retail_Magoinx
9	T10910	03/06/2016	61.3845	Indianapolis	Liancheng	STR10016	39.719605420296	-88.29415959839E ·	Name
10	T10914	02/14/2016	31.5	Indianapolis	Liancheng	STR10016	39.719605420296	-86.204150598399	Hann Contra
11	T10918	02/22/2016	33.576	Indianapolis	Liancheng	STR10016	39.710605420296	-86.29415959839£ +	Description
12	T10904	02/08/2016	90.264	Chicago	Lijiang	STR10010	41.97958694069	-87.90574573209	
13	T10657	03/05/2016	71.5095	Boston	Luxi	STR10006	42.363629345993	-71.010039231911	
14	T10641	02/14/2016	95.316	Chicago	Liancheng	STR10010	41.97958694069	-87.90574573269	 Model Options
15	T10645	04/29/2016	48.735	Chicago	Liancheng	STR10010	41.97958694069	-87.90574573269	Fnable Planning
16	T10649	03/03/2016	73.4265	Chicago	Liancheng	STR10010	41.97958694069	-87.90574573269	Elit anninable events ID cells with a default value
17	T10889	02/03/2016	111.528	Chicago	Liancheng	STR10010	41,97958694069	-87.90574573269	The supportance and a to come state a second states
18	T10893	02/27/2016	72.95	Chicago	Liancheng	STR10010	41,97958694069	-87.90574573269	Default Carrency for Model USD
19	T10897	02/02/2016	91.38	Chicago	Liancheng	STR10010	41.97958094069	-87.90574573269	
20	T10652	03/14/2016	92.097	Houston	Dunhuang		29.975601167888	-95.326360908245 +	
21	T10921	02/18/2016	45.204	Houston	Dunhuang	STR10015	29.975601167888	-95.326360908245 +	
22	T10651	03/16/2016	50.2245	Houston	Changzhi	STR10015	29.975601167888	-95.326360908245	Cruite Model

PICTURE 5. The Modeler displays data in rows and columns (Nguyen 2020)

Regarding types of data models, Sidiq (2022) mentioned that SAC offers datasets, analytics models, and planning models. Depending on the required activities, the model is used based on its specific characteristics.

Firstly, a dataset is a simple collection of data. Typically, data displays as a table. The dataset uses for creating the foundation of stories as well as data sources for Smart Predict. Therefore, this type is the best option for users who need to produce stories or visualizations but do not want to dive into defining the structure during processing data or when development does not require IT governance. (SAP Help Portal, page "About Datasets and Dataset Types".)

Secondly, an analytics model represents data and enriches this data with extra information, such as hierarchies or authorizations. Also, the definition of additional measures or groupings of dimension members is allowed in the analytics model. Generally, an analytics model follows a standard structure that typically includes data sources, supplementary information of the model, and dimensions such as the Account dimension or the optional Date dimension. Furthermore, users can activate additional features like data access control over particular dimensions and performance enhancements. (Sidiq 2022.) Finally, a planning model is similar to an analytics model in general. However, it is an extended analytical model with some capabilities that play essential roles in planning activities and the creation of planning workflows. (Sidiq 2022.) With the functionalities of this model, business users can plan and forecast based on various planning hypotheses and observe the financial impact instantly (Kennedy 2020). In addition, the planning model contains Time, Category, Account and Organizational dimensions (Sandepogu 2017).

Regarding "stories", business users can utilize "stories" to visualize and explore their data for reporting, planning, and analysing. Data view and pages are the two main sections within "stories". Each story can have several pages which are organized as a grid or canvas view. In picture 6, the created "stories" in SAP Analytics Cloud include four pages and data are presented to various views like tabular graphical and charts. Also, "stories" can be referred to as a dashboard. (SAP Community 2019.)



PICTURE 6. A created story in SAP Analytics Cloud (SAP Community 2019)

Moreover, "stories" allow for great creative freedom and are adaptable for both creators and viewers. It also enables creators to determine how interactive "stories" will be and which features will be offered to viewers. (Sidiq 2022.)

"Stories" of SAC provide clients with significant advantages. At first, "stories" support users to get hidden insights within the business data (SAP Community, page "Stories, Reporting, and Data Exploration"). Then, it also benefits users to discover actionable insights in real-time data. Moreover, the "stories" provide an effective and integrated analytics-as-a-service tool and help in advanced predictive analytics. In addition, it offers collaborative enterprise planning and supports the making-decision process fast and more confidently. (SAP Community 2019.)

3 RESEARCH METHOD

This chapter aims to present the research method conducted in this report, the research objects and the research questions to analyse a case company using SAP Analytics Cloud for visualizing data and detecting problems.

The research method used for this study is qualitative research. This approach develops in the social sciences to allow researchers to study social and cultural phenomena. Action research, case study research, and grounded theory are approaches to this method. In addition, the data sources of qualitative research come from observation and participant observation, interviews and surveys, documents and texts, and the impressions and reactions of researchers. (Myers 2009.)

3.1 Case Study Research

In detail, qualitative – case study research is the approach for the topic of this study. According to Myers (2009), case study research can be used for exploratory and explanation-specific topics. While some features, factors, or issues can be discovered and applied in similar situations in exploratory-specific research, explanation-specific research can be used for testing or comparing theories. Moreover, it is also used to develop some causal explanations.

A common feature of the case study research concentrates on "what" is studied instead of "when" in processing research. Therefore, this research method can be applied at any stage of the research's development. Essentially, case study research in the business world exploits empirical evidence from real people in real-life organizations. Then, by asking and answering questions "how" and "why", researchers will understand why and how processing the making-decision or operating the business processes in an enterprise. Thus, researchers are without any purposeful interventions in case studies; alternatively, they can look for obvious cases, describe, and use these cases to serve their research's purposes. (Myers 2009.)

This report uses participant observation as a data collection technique. Myers (2009) continued to define participant observation as when a researcher does not only take an observer role but also plays a participant role in the organization's activities by attempting to discuss and interact with people to gain better comprehension from the inside. Again, Jorgensen (1989) defined in the quick way that participant observation in case studies is carried out when a researcher tries to describe a phenomenon of a research problem comprehensively and exhaustively.

The report is presented from a participant observer perspective. The data visualization and data analysis of a case company are described in detail, starting from selecting data to presenting the findings and solutions.

3.2 Research Objectives and Research Questions

Research objectives specify the research topic in detail based on the research aim. Typically, the research topic has two or three objectives (Thomas & Hodges 2010). The outcomes expectation of this research study is to determine research objectives.

The research objectives of this study are:

- Objective 1: To examine the benefits of SAP Analytics Cloud in the case company's day-today activities, decision-making, and predictive planning.
- Objective 2: To explore which functionalities of this software are highlighted.

Three research questions are discussed to identify the objectives of this report. And the answers will be sought by observing the benefits the case company gained when using the SAC software. Three questions are:

- Question 1: How does SAC support the case company to detect the problems they were facing?
- Question 2: How does SAC benefit for the case company's data performance and data analysis?
- Question 3: How does SAC improve the case company's decision-making

4 CASE COMPANY ANALYSIS

As discussed above, SAP Analytics Cloud is a top-of-the-line Software as a Service (SaaS) solution that unifies all analytics features: planning, predictive, business intelligence, and so on in a one-stop that is designed based on the user interface, allowing users to save time and effort, and also enhancing the decision-making process.

Therefore, to answer three research questions about how SAP Analytics Cloud supports and benefits the company in its operation and improves the decision-making process. This report will simulate the steps of implementing the SAP Analytics Cloud within the case company.

The case company is called Fond Rouge. They were dealing with problems when penetrating a new market - The United States after achieving notable successes in its key market - European.

The tasks are to use these three datasets to explore issues of Fond Rouge in the US by following steps: data selection, data wrangling, data visualization, and data analysis, then presenting the results of the findings and proposing the solutions.

4.1 Case Company Background Information

A company gains more percentage shares of a product or service used by consumers compared to the current market shares in the total estimated market of that product or service is considered as the market penetration strategy (Kenton 2023). Thus, organizations following the market penetration strategy will seek the opportunities to grow their existing products or service (Robertson 2013). To expand a sizeable market share, the company should launch a product or service and enter the market as rapid as possible (Luo & Zhao 2014).

The board of Fond Rouge, a French shoe company, decided to cross the pond and venture into the new footwear market, North America after seeing significant success in the European market. At the beginning stage, the penetration strategy in the new market goes as planned, with even more optimism than their prediction. Therefore, Fond Rouge keeps going to scale retail locations more quickly. However, in this optimistic situation about this ongoing success, the company leads have missed a significant

trend is rising in the organization's data. A stream of negative reviews online, primarily on social media, is emerging until the marketing team raises awareness about it.

After many meetings, the Business Development department and the Head of Engineering make the conclusions. They believe that counterfeit or poor-quality products are affecting US sales. It is the main reason that leads to those negative reviews online. As a result, identifying the issues, consulting the best way to narrow the affected locations, and proposing solutions are requested.

4.2 Data Selection and Data Wrangling

Putting data in the specific context plays a vital role in the efficiency of data analysis. Without context, data is meaningless and any created data visualization will become useless. Therefore, understanding data before knowing what it represents will help communicate with data effectively. The more effective communication established, the more comprehensive visualization and analysis had. (Yau 2013.)

Following Yau (2013), users should answer questions centring around who, what, when, where, why and how to get a complete understanding. Then, data will be well-chosen and well-prepared based on that understanding.

After acquiring a sufficient understanding of data context by answering specific questions, the next step is to determine the "right data" for troubleshooting business problems. Then, the chosen data will be cleaned and pre-processed for the following steps - data modelling and data analysis.

4.2.1 Data Selection

Faculty Development and Instructional Design Centre at Northern Illinois University (2005) defined data selection as a process of the proper data type, source, and collected data tools determination. Plant & Bohm (2010) stated that the data needs to be chosen carefully as an initial step. Semantically, the selection of high-quality data matching the discovery process's objective plays an essential role in the following steps. Data availability, quality, type, format, and semantics are a few examples of the selection criteria.

This section is to identify the appropriate data type. Picture 7 to picture 9 are the samples of the most common data types that Fond Rouge would usually collect.

- Sales examples for sales transactions
- Returns examples for order return transactions
- Sentiment a score of 0-100 generated from a combination of the Net Promoter Score (NPS) the client measures and sentiment score of public mentions on social media

OrderID	Date	Country	City	Latitude	Longtitude	ProductCategoryName	ProductID	Product	Quantity I	Discount	Price	Status	_
order-fd7c3c2a-f481-4d58-91b6-06a9e2de0724	2020/11/7	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-b7c06d0a-977d-497b-ae3e-95b58985cafd	Amélie	7	2,65	40	COMPLETED	
order-74ff7daf-2d0a-4dae-b132-58a12fc42d24	2020/11/7	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-7bef3e02-033c-4259-93da-a25f4f7169be	Claudette	5	6,21	102,95	COMPLETED	
order-0587ebd4-4a63-45f8-8d86-a8d2e814a10a	2020/11/19	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-98f22154-ee97-4ef8-be84-7283cec0ebad	Bridgette	2	0,58	39,95	COMPLETED	
order-bf7d5289-d4c1-4cca-b054-e4a4817eb8f8	2020/11/7	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	10	1,7	46,93	COMPLETED	
order-1c0c517f-2d62-4278-940b-f8023b19a4e3	2020/11/15	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-fa4a41fc-4a31-44b5-953f-8e2a45b43673	Cecile	1	1,03	78,56	COMPLETED	
order-7c2413bf-34ef-468d-bc25-7aea183b2fd1	2020/11/1	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-fa4a41fc-4a31-44b5-953f-8e2a45b43673	Cecile	4	4,61	78,56	COMPLETED	
order-b0639802-c23d-49f7-81e5-65c576fd5d9b	2020/11/26	Denmark	Copenhagen	55.6786	12.5635	Flats	product-0a97c64c-582b-41a9-b367-2a4e081cf3d5	Estelle	7	4,53	45,61	COMPLETED	
order-0bea9af6-8791-4915-8ef5-2901dd70e3a2	2020/11/26	Denmark	Copenhagen	55.6786	12.5635	Brogues	product-a19d1434-d5f2-4a2a-9fe0-7d70f63e391e	Denis	4	3,56	58,95	COMPLETED	
order-29377f15-69ac-4b18-a968-632f848c066e	2020/11/13	Denmark	Copenhagen	55.6786	12.5635	Flats	product-9f6a916a-271c-4d78-9e5f-f802bbcf6548	Adele	10	1,82	35,9	COMPLETED	
order-fc3e5cf3-267e-49fa-af66-f9f86c341d1c	2020/11/9	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	3	0,3	46,93	COMPLETED	
order-c9f13c1e-6907-46f4-925c-e8788fbdadef	2020/11/11	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-f7e07591-2598-4615-82c2-34f6ad248e50	Eloise	8	4,18	80,95	COMPLETED	
order-2520c1f6-b354-4162-a1bc-eb5a9923299c	2020/11/26	Denmark	Copenhagen	55.6786	12.5635	Flats	product-f709c12a-ffe5-48b1-a3d2-f247acf8e176	Danielle	5	0,5	36,46	COMPLETED	
order-725ff9a0-dae1-4cf3-a9a3-678bb8fa7af9	2020/11/16	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-7bef3e02-033c-4259-93da-a25f4f7169be	Claudette	9	8,42	102,95	COMPLETED	
order-f2efe036-f9ab-4cbe-ad54-6798947f95bb	2020/11/28	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-b7c06d0a-977d-497b-ae3e-95b58985cafd	Amélie	3	0,62	40	COMPLETED	
order-bd9985f8-50d5-4111-acce-c055a900e2ac	2020/11/8	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-f7e07591-2598-4615-82c2-34f6ad248e50	Eloise	1	5,09	80,95	COMPLETED	
order-9690d5a3-ca4c-4bff-84f2-4c0bed15d015	2020/11/22	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-fa4a41fc-4a31-44b5-953f-8e2a45b43673	Cecile	7	4,29	78,56	COMPLETED	
order-a7b29299-c15c-483d-b0cc-6bcaba352b2d	2020/11/3	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-b7c06d0a-977d-497b-ae3e-95b58985cafd	Amélie	9	2,43	40	COMPLETED	
order-0a3c5406-bb50-4d55-b3aa-970983328861	2020/11/18	Denmark	Copenhagen	55.6786	12.5635	Stilettos	product-fa4a41fc-4a31-44b5-953f-8e2a45b43673	Cecile	9	7,03	78,56	COMPLETED	
order-f0ba6486-ca04-4184-98b8-3e2ef8f2b264	2020/11/12	Denmark	Copenhagen	55.6786	12.5635	Brogues	product-a19d1434-d5f2-4a2a-9fe0-7d70f63e391e	Denis	9	4,04	58,95	COMPLETED	
order-68b41bfc-ab5f-461f-bbfd-1b4576e79fc2	2020/11/20	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-98f22154-ee97-4ef8-be84-7283cec0ebad	Bridgette	9	3,75	39,95	COMPLETED	
order-d8690714-c091-4306-bd05-a128ee11536c	2020/11/10	Denmark	Copenhagen	55.6786	12.5635	Flats	product-0a97c64c-582b-41a9-b367-2a4e081cf3d5	Estelle	2	0,85	45,61	COMPLETED	
order-897bfa40-a732-4aa3-b0f0-1b620fac2879	2020/11/21	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	7	3,28	46,93	COMPLETED	
order-a4e07f12-db55-4f7c-99eb-8247ff67f162	2020/11/9	Denmark	Copenhagen	55.6786	12.5635	Platforms	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	2	3,81	46,93	COMPLETED	
order-afb0c417-e992-405a-98ae-93a0e9d7e503	2020/11/1	Denmark	Copenhagen	55.6786	12.5635	Flats	product-9f6a916a-271c-4d78-9e5f-f802bbcf6548	Adele	1	2,68	35,9	COMPLETED	

PICTURE 7. A sample of sales transactions data (SAP Technical Consulting Virtual Internship Program)

OrderID	Status								
order-8cacb48a-6a1e-42de-abe2-cf6092a48af2	RETURNED								
order-f696bafe-acd9-4985-a4ad-05da86cc8268	RETURNED								
order-3c18c650-b023-4b3e-bc03-e6ae455329ff	RETURNED								
order-6b940800-f65e-4717-ac18-bd12e0e91400	RETURNED								
order-766719c3-2fe4-4fc9-8d44-26c10a575ea2	RETURNED								
order-b907a311-240c-4d3d-a7b6-9af66bbab758	RETURNED								
order-064459d9-d81d-4410-9320-8097de3804e1	RETURNED								
order-e31cc2fa-31c1-4cd8-a78b-53e9a5da78b2	RETURNED								
order-2b1dd889-0702-45dc-a2f9-6a1c9fd3e738	RETURNED								
order-c51aca32-1435-456e-a890-abe7e22626d2	RETURNED								
order-0d2e9495-c37a-4d9a-94b6-0bdbd90b8190	RETURNED								
order-a5f95e0d-e2a3-4d3d-8b96-ec8caf3c509a	RETURNED								
order-33677257-805a-4b99-b41d-a32517d2ac26	RETURNED								
order-5d4f7bd9-b6c8-42e6-b345-31da3db5bdc5	RETURNED								
order-7b3a6b73-80c1-467a-a283-6efc5d751c57	RETURNED								
order-c44c159c-dabc-47df-ae35-43658617f053	RETURNED								
order-5a843fb3-7af6-4053-ab31-03bd5c17937a	RETURNED								
order-965f033c-6a8e-4a3c-8ee7-5e531346e425	RETURNED								
order-9aa8df5a-ceaa-4753-b728-3f108fdee5d5	RETURNED								
order-c363bc06-b6d5-4691-ad9f-d889c8484c44	RETURNED								
order-7b91550a-d9f0-44e7-8dcf-b86106949cda	RETURNED								
order-f670ccc8-fc2c-4696-bceb-efaa1782b5ce	RETURNED								
order-ee214545-1ca5-4c70-bfd3-f5b08b5a7dc1	RETURNED								
order-c69d3979-2f00-4460-b422-0133a9e7f6fa	RETURNED								

PICTURE 8. A sample of return transactions data (SAP Technical Consulting Virtual Internship Program)

Regarding Net Promoter Score (NPS) mentioned in the sentiment data sample, it is a measurement used in customer experience programmes. NPS measures and tracks how loyal customers are to a business. The scores of NPS are calculated and reported in the range between -100 and + 100 by using a single-question survey: "How likely is it that you would recommend [Organization X/Product Y/Ser-

vice Z] to a friend or colleague?". (Qualtrics 2022.) The NPS scores of company's customer satisfaction are computed from 0 to 100 in which 0-64 is considered negative, 65-84 is neutral, and 85-100 is positive.

Year_Month	Location_ID	ProductID	Product	Sentiment Class						
2019/3	Belgium, Brussels	product-20700833-fc84-4340-9a59-669fe6acc94b	Antoine	92 POS						
2019/3	Belgium, Brussels	product-124ef52a-c7c3-48af-b315-33a14b2f6e1d	François	87 POS						
2019/3	Belgium, Brussels	product-a19d1434-d5f2-4a2a-9fe0-7d70f63e391e	Denis	83 NEU						
2019/3	Belgium, Brussels	product-9f6a916a-271c-4d78-9e5f-f802bbcf6548	Adele	87 POS						
2019/3	Belgium, Brussels	product-f709c12a-ffe5-48b1-a3d2-f247acf8e176	Danielle	90 POS						
2019/3	Belgium, Brussels	product-0a97c64c-582b-41a9-b367-2a4e081cf3d5	Estelle	83 NEU						
2019/3	Belgium, Brussels	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	88 POS						
2019/3	Belgium, Brussels	product-b7c06d0a-977d-497b-ae3e-95b58985cafd	Amélie	88 POS						
2019/3	Belgium, Brussels	product-98f22154-ee97-4ef8-be84-7283cec0ebad	Bridgette	85 POS						
2019/3	Belgium, Brussels	product-f7e07591-2598-4615-82c2-34f6ad248e50	Eloise	87 POS						
2019/3	Belgium, Brussels	product-fa4a41fc-4a31-44b5-953f-8e2a45b43673	Cecile	83 NEU						
2019/3	Belgium, Brussels	product-7bef3e02-033c-4259-93da-a25f4f7169be	Claudette	84 NEU						
2019/4	Belgium, Brussels	product-20700833-fc84-4340-9a59-669fe6acc94b	Antoine	88 POS						
2019/4	Belgium, Brussels	product-124ef52a-c7c3-48af-b315-33a14b2f6e1d	François	92 POS						
2019/4	Belgium, Brussels	product-a19d1434-d5f2-4a2a-9fe0-7d70f63e391e	Denis	89 POS						
2019/4	Belgium, Brussels	product-9f6a916a-271c-4d78-9e5f-f802bbcf6548	Adele	92 POS						
2019/4	Belgium, Brussels	product-f709c12a-ffe5-48b1-a3d2-f247acf8e176	Danielle	83 NEU						
2019/4	Belgium, Brussels	product-0a97c64c-582b-41a9-b367-2a4e081cf3d5	Estelle	86 POS						
2019/4	Belgium, Brussels	product-642f72ba-c5d6-4126-be0f-a22fe4e9fbb6	Bella	89 POS						
2020/12	Portugal, Lisbon	product-7bef3e02-033c-4259-93da-a25f4f7169be	Claudette	92 POS						
2021/1	Portugal, Lisbon	product-20700833-fc84-4340-9a59-669fe6acc94b	Antoine	86 POS						
2021/1	Portugal, Lisbon	product-124ef52a-c7c3-48af-b315-33a14b2f6e1d	François	86 POS						
2021/1	Portugal, Lisbon	product-a19d1434-d5f2-4a2a-9fe0-7d70f63e391e	Denis	91 POS						
2021/1	Portugal, Lisbon	product-9f6a916a-271c-4d78-9e5f-f802bbcf6548	Adele	90 POS						

PICTURE 9. A sample of sentiment data (SAP Technical Consulting Virtual Internship Program)

The context of this analysis is the emerging tendency of negative reviews primarily from social media after Fond Rouge entered the North American market. Counterfeit or poor-quality products could be the main reasons causing those poor reviews. As a result, the sales are reducing.

Based on the data context, the sales transactions, returns of products, and sentiment scores in every location for every product are selected. There are statistical datasets since the datasets are formatted into a .xlsx file. However, these are valuable datasets for investigating Fond Rouge's problems. Of course, we use SAC software for analysing those.

4.2.2 Data Wrangling

Data modelling will start with data wrangling, also known as data preparation. This step is where the data is mapped, cleaned, transformed, and prepared for analysis. YouTube video: (Data Preparation in SAP Analytics Cloud 2017.)

In the data wrangling section, we combine these selected datasets into one file and rename it to "company_data.xlsx", which includes the Sales sheet, Return sheet, and Sentiment sheet. Next, the "company_data.xlsx" is imported to SAP Analytics Cloud (SAC). SAC offers various imported ways, such as "From CSV or Excel file", "Live Data Model", and "From a Data Source" options. We choose the "From a CSV or Excel File" option since "company_data.xlsx" is an Excel file.

At first, the imported data process is started with Modeler. Picture 10 illustrates the process of importing the Sales sheet into SAC.



PICTURE 10. The process of importing the Sales sheet into SAC

Then, picture 11 shows the process of uploading the Returns sheet into SAC. In particular, OrderID is the combination key between the Sales sheet and the Returns sheet.

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PICTURE 11. The process of importing the Returns sheet into SAC

Unlike matching the Sales and Return sheets based on the OrderID as the key combination, matching the Sentiment sheet with the Sales sheet requires some preparation. We need to generate two new columns for connecting these two sheets. Until then, we can import the Sentiment sheet into the SAC. Two built new columns will be named Year_Month and Location_ID.

Initially, we extract the Year_Month from the Date column by applying the Extract Formula. Then, we rename the new column to Year_Month. And then, we continue to build the Location_ID column. It is necessary to duplicate the Country and City columns to combine them later as the Location_ID. After that, we use the concatenate columns with the "," function to separate them. Lastly, we rename the new column to Location_ID. Eventually, we can match the Sales and Sentiment Sheets by linking the key combinations: Location_ID, Year_Month, and ProductID. Picture 12 displays the process of extracting the Year_Month, while picture 13 shows the process of forming the Location_ID. Picture 14 performs the steps of importing the Sentiment sheets into SAC. Most importantly, we must ensure the selected columns have the same name and same order on both sides when importing the Sentiment sheet.

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PICTURE 12. The process of exacting Year_Month column from Date column

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PICTURE 13. The process of forming Location_ID from Country and City columns

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PITURE 14. The process of importing the Sentiment sheet into SAC

At present, we imported three needed data sheets into SAC successfully. Sales, Return, and Sentiment sheets are available at SAC software. However, we need to clean the data sources to ensure they are ready for data visualization and analysis later. Although data cleaning takes time, the cleaner the data, the more accurate the visualization and analysis.

The following steps will show the cleaning data process. At first, we will link the Product to the ProductID as the Description. Next, we will define the parent and child roles for pairs: the ProductCategoryName - ProductID and the Country - City. And, we create the Parent-Child Hierarchy for them. Then, we combine the Latitude and Longitude columns as Location. After that, we replace the "COM-PLETED" status with the "RETURNED" status for the returned orders. We continue to calculate the Revenue and Refund columns. At last, we check the properties of all columns to ensure they are in the correct data types.

SAP Analytics Cloud supports two modes of view: Table view and Card view. In this step, the Card View is used to assign the attributes of specific columns. Because the ProductID needs a Description, we add the Product as the Description dimension to the ProductID. Picture 15 illustrates the process of assigning and linking the Product to ProductID as its description attribute.



PICTURE 15. The process of assigning and linking Product to ProductID as its description

ProductID belongs to ProductCategoryName. We describe this relationship by adding a Parent-Child Hierarchy with ProductCategoryName playing the parent role and ProductID playing the child role. We can recognize the change by checking the icon at the top right corner. Picture 16 performs the process of connecting the Parent - Child Hierarchy between ProductCategoryName and ProductID.



PICTURE 16. The process of pairing the Parent-Child Hierarchy for ProductCategoryName and ProductID

Similarly, the Country and City also connect as a Parent-Child Hierarchy; therefore, pairing these two columns process is the same as the pairing ProductCategoryName and ProductID process. In this case, the Country plays as Parent role, and City plays the Child role. Picture 17 shows the process of pairing the Parent-Child Hierarchy for Country and City.



PICTURE 17. The process of pairing the Parent-Child Hierarchy for Country and City

According to Kwok (2022), the Geo Map widget allows users can analyse their geographic data by overlaying multiple layers of business data on Geo Map with detailed information. Therefore, we will use Latitude and Longitude to geo-enrich and plot data on a map. Picture 18 is the process of combining Latitude and Longitude and naming to Location. This combination can support us in gaining an overview picture of our businesses.

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PICTURE 18. The process of combining Latitude and Longitude to Location

Taking an overview of our dataset, we can see several unintelligible and repeated columns: Status -Status_2 and Product - Product_2. While the Status_2 column represents the orders returned by customers, the Product is representative of the finished transactions. Therefore, we initially need to replace the returned OrderID situation with "RETURNED" instead of "COMPLETED" by using Replace Smart Transform with a Where clause (Replace Cell in [Status] matching "COMPLETED" with "RE-TURNED" Where [Status_2] is "RETURNED"). Picture 19 will describe the process of replacing and updating the status for the returned OrderID. The result after the change will be the current situation of returned orders and the completed orders displayed in the same Status column. Now, we delete unnecessary columns to avoid repeating information in our dataset. In this case, we will remove the Status_2 and Product_2 that repeats the Product column. The deleting steps are in picture 20.

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PICTURE 19. The process of replacing the completed to returned status for the returned orders

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PICTURE 20. Deleting Status_2 column

In order to grasp the business situation of Fond Rouge in every single market, especially in the US, we calculate the revenue and refund for each country and city. It helps us to know which country brings us

strong or poor sales and which has a high rate of returned orders. From that, we can develop comprehensive strategies to improve or narrow down.

All needed steps for calculating Revenue and Refund are in picture 21. To compute the revenue, we use the formula [Price] * [Quantity] - [Discount]. Meanwhile, we use IF () to calculate the refund: IF ([Status] = "RETURNED", [Revenue], 0). It will let us know which retailers have high returned orders. Ultimately, we have two new calculated columns in our dataset: Revenue and Refund.



PICTURE 21. The process of calculating revenue and refund

Last, we check the properties of all columns in the dataset to ensure they are in the correct data types. It is also the final step in this data-cleaning section. We make adjustments for Year_Month, Latitude & Longitude and Sentiment. At this point, the Year_Month column should be a Date attribute instead of a Generic Dimension. Conversely, Latitude & Longitude is a Generic Dimension. Likewise, we change the Sentiment to a Measure because we will use it to calculate the sentiment score later.

After completing the data cleaning, the next step is to generate a Model by clicking the "Create Model". Then SAC will validate the dataset. If the dataset is without any issues, SAC will create the Model. We name it to be X_Data_Model. Picture 22 and picture 23 present the processes of adjusting data types, creating a model and showing the workspace of the model structure.

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PICTURE 22. The steps of re-defining the data type of Year_Month column

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PICTURE 23. The process of validating, confirming and creating X_Data_Model

4.3 Data Visualization and Data Analysis

Previously, we finished the data cleaning. The clean dataset is available for further steps: data visualization and analysis. We recognize that analysing data will be more efficient if the dataset can be depicted as graphs, charts, and geo-maps rather than in table forms. Thus, we use column & line, donut, stacked bar, and geo map to plot revenue, refund, and sentiment class. Also, we calculate the refund/revenue ratio and average sentiment score for further clarification of the later analysis. For the analytical scope, we decide to start from the country and narrow it down to the city level. Picture 24 to picture 39 are the results after data visualization.

Afterwards, we analyse in depth by questioning in connection with the issues shown in the graphs. Several questions arise: In which city does Fond Rouge lose the highest percentage of revenue due to returns? How many percentages of Negative class (NEG) are in the US? Where can we suspect to face fake products? Does the problem pose in all locations in the US? Is only the counterfeit issue detected in the Fond Rouge dataset? Is there anything else?

4.3.1 Data Visualization

SAC provides users with four types of stories: Responsive, Canvas, Gird, and From a Smart Discovery. We select a canvas setting for building the stories in this report. At first, we choose a Chart as the first object to add to our story canvas. As we can see in picture 24, besides the Chart option, the canvas setting offers various options, such as Table, Shape, Geo Map, Image, and Text.

We use the Combination Column & Line chart type to present the revenue and refund of Fond Rouge globally. Picture 25 displays the settings of the chart. While the column axis is the revenue at the country level, the line axis represents the refund of each country. The city is the chosen dimension, with level 1 being the country and level 2 being the specific city. In picture 26, we can see France accounts for the highest revenue. Although sales in the US are ranked third, the refund is the highest.



PICTURE 24. The process of building the Stories in canvas settings



PICTURE 25. The settings of the combination column & line chart type for plotting revenue and refund globally



PICTURE 26. The refund and revenue per country

Moreover, we also use the Calculations functions available in SAC to compute the refund/revenue ratio for providing a basis for countries' comparison. Besides the settings of the calculation and the refund/revenue bar chart shown in picture 27, picture 28 gives us the rate refund/revenue overview. In picture 29, the US has the highest ratio - 0.18 while Switzerland accounts for the lowest rate - 0.01. In addition, we can click on a particular column to see more detail. The software can also measure the difference automatically between columns.



PICTURE 27. The settings of refund/revenue ratio calculation

(FK) (***

Refund/Revenue per Country



PICTURE 28. The refund/revenue ration per country



PICTURE 29. The refund/revenue ratio gap between the highest and lowest country

FK

We continue to measure the sentiment based on the global number of sales. It includes three classes: positive (POS), neutral (NEU), and negative (NEG). In picture 30, POS accounts for 76.86% of the donut chart, NEU is 18.89%, and NEG is the smallest part - 4.25%. It means that Fond Rouge still maintains positive feedback from customers in general. Nevertheless, we dig deeper into the NEG class to confirm where to derive the negative comments.



PICTURE 30. The sentiment class based on number of sales globally

Thus, it is necessary to calculate the average sentiment score. Picture 31 shows the required steps to compute the average sentiment score based on OrderID. We also combine the average score with the refund/revenue ratio to get a better view. In picture 32, the US draws our attention. We can notice that the average score of other countries is above 87, except the US. It has the lowest average score - only 76.12 while getting the highest refund/revenue ratio.



PICTURE 31. The settings of average sentiment calculation



PICTURE 32. The refund/revenue ratio and average sentiment per country

After going through all graphs, we can see that Fond Rouge has problems in the US operation. Therefore, we drill further to understand the operation in cities of the US.

Specifically, we plot the refund and revenue of each city on a stacked bar. Picture 33 shows us the steps of drawing the bar chart, and picture 34 is the final chart to present the refund and revenue account in total. New York has the highest sales, and Las Vegas has the lowest. Despite the highest refund accounted for by New York, San Diego causes our concern. The returned money of San Diego accounts for over 35% of the total revenue, while only 14% in New York.

	Page 1							💥 Builder	۵
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8				Refund	Revenue			Currently Selected Chart	×
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Å	Las Vegas	30,357.59	31,843.88					Show Chart as 100%	Country
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PICTURE 33: The stacked bar chart settings of the refund and revenue per city in the US



PICTURE 34. The refund and revenue per city in the US

Moving to assess the sentiment class in the US, a donut chart confirms our concern. In picture 35, the NEG class is 30.66% and POS only 49.81%. The gap between negative and positive feedback is not too broad. It could be not only the adverse comments come from San Diego but also the other cities.



PICTURE 35. The sentiment class based on number of sales in the US

Again, we calculate the average sentiment score and rate of refund/revenue of each city in the US. Picture 36 shows that Las Vegas and Los Angeles are facing a poor average sentiment score same as San Diego. However, the refund/revenue ratio is in the lowest range - 0.05 and 0.07. It seems the US operation is struggling with more than one matter.



PICTURE 36. The refund/revenue ratio and average sentiment per city in the US

Lastly, we go through the Geo Map from picture 37 to picture 39. Based on the size of the bubbles, we can evaluate the magnitude of the revenue, refund/revenue ratio, and average sentiment score. It is one of the advantages when using Geo-Map. In picture 37, the three biggest bubbles are in London, Paris, and Rome, which means those three cities have the highest sales. By contrast, in picture 38, we know San Diego has the highest rate of returned orders because of its bubble size. Similarly, the bubbles of

picture 39 point out that Los Angeles and Las Vegas are two cities which have the lowest average sentiment score.



PICTURE 37. The geo-map of revenue globally

Location (Refund/Revenue)		(FL) (***)
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Verdoover Verdoover San Fallotez		
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> LEGENDS	NIGERIA Acora	Bangk

PICTURE 38. The geo-map of refund/revenue ratio globally



PICTURE 39. The geo-map of average sentiment globally

4.3.2 Data Analysis

The data visualization in the previous steps helps us understand the current situation better. Several analytics questions are answered based on the created stories. Those questions are:

In which city does Fond Rouge lose the highest percentage of revenue due to returns?

San Diego has the highest number of returned orders. Therefore, it is the city that causes the most losses in the turnover of Fond Rouge.

How many percentages of Negative class (NEG) are in the US?

The negative class in the US accounts for 30.66%.

Where can we suspect to face fake products?

It is in Los Angeles and Las Vegas. These two cities have a poor sentiment score and low refund/revenue ratio. After buying the counterfeit products, customers can not return purchased products to the retailers. They do not have any transaction records of sold products. Therefore, the return is not allowed.

Does the problem pose in all locations in the US?

Fortunately, no. The counterfeit problem happens only in Los Angeles and Las Vegas. Except for San Diego, the others still demonstrate a high average sentiment score - over 87. Moreover, New York and Atlanta have high turnover with low refunds.

Is only the counterfeit issue detected in the Fond Rouge dataset? Is there anything else?

The fake products in Los Angeles and Las Vegas are not the only problem confirmed in the Fond Rouge dataset. We realize that San Diego also caused our concern. It has the highest refund/revenue ratio and the lowest sentiment score. We believe it is related to the poor-quality products. Customers bought the inferior products and wanted to return it. As a result, it leads to a high refund/revenue ratio and a low satisfaction level in San Diego.

4.4 Findings Results and Next Steps Suggestions

After using SAC to visualize data and answer analysis questions to detect the problems that dominate in the Fond Rouge dataset, we will present findings and propose some solutions in this last section.

4.4.1 Findings Results

When Fond Rouge expands their business into North America, they get positive feedback at the beginning stage. However, they notice the negative trend increases from social media. They suspect that they face counterfeit products in the US operation.

Then, they use SAC to plot its data to confirm their doubts. After going through the visualization and analysis, we conclude that France contributes the highest revenue to the total turnover of Fond Rouge. Switzerland has the lowest refund/revenue ratio. However, we acknowledge that the US has the highest refund. In addition, the US has the highest refund/revenue ratio and the lowest average sentiment score. All graphs prove that the US is facing problems. Fortunately, Fond Rouge still obtains much positive feedback from customers globally.

After investigating the problems in the US, we narrow the scope around the US. Combined with measuring the sentiment class, we realize that two issues arise in the Fond Rouge dataset: counterfeit and inferior products. Based on the rate of refund/revenue and average sentiment score, we identify that Los Angeles and Las Vegas confront fake products, while San Diego encounters poor quality products. At present, we have an overview of the US situation. Immediately, we propose some solutions to limit the negative impact and minimize the damages to Fond Rouge.

4.4.2 Next Steps Suggestions

As the findings are presented previously, I suggest several steps to narrow down the adverse impact of counterfeit and inferior products in US retailers.

Initially, Fond Rouge should investigate its product lines relevant to two defined problems. In addition, Fond Rouge can also use SAC to inspect product categories that cause a high refund/revenue ratio.

Next, we examine the inferior product issue in San Diego. The customers return the purchased products because of the bad quality. Therefore, based on returned records, Fond Rouge should contact those customers as soon as possible to conduct interviews. The interview's purpose is to uncover the reason behind the poor-quality products. Fond Rouge can offer prizes for participants to encourage them to respond to surveys. Besides, Fond Rouge can test the whole order process with secret customers to recognize the inadequacies within the order cycle. Thereby, Fond Rouge can improve its customer service.

Then, to tackle the counterfeit problem in Los Angeles and Las Vegas, Fond Rouge should re-evaluate those negative reviews seriously. The marketing department should contact the customers who left negative comments on social media. It can help to confirm they are real consumers instead competitors launching campaigns to hurt the Fond Rouge's image. Moreover, the marketing department should stop and not allow customers without actual purchases the ability to continue leaving adverse comments.

Above are some suggestions to narrow down the affected retailers in US operations caused by poorquality and counterfeit products. At the same time, the team can schedule the SAC task to continuously record the updated data for existing models and stories from a newer version of the spreadsheets.

Lastly, to improve the decision-making process and reduce the spreadsheets, Fond Rouge can select the database solution. It allows the data sources to integrate more quickly and to update in real-time.

With real-time data, Fond Rouge can make a decision faster and more precisely, adapt better to the market fluctuations, enhance operation productivity, and many other great benefits that Fond Rouge can gain from it.

5 CONCLUSION

Today, we are witnessing significant changes in the business landscape and higher expectations from customers. There is no doubt that data analysis plays a crucial role in optimizing business performance and satisfying customer requirements. Also, we cannot deny a predictive planning role in supporting enterprises to make better decisions. The more precise the predictive planning is, the better the outcomes will be. In addition, predictive planning can help organizations avoid making costly mistakes or losing golden opportunities. Therefore, SAC fulfils current business operations requirements to increase competitive advantages in the data-driven era.

By going deeply into the case company, we can see Fond Rouge reaps the benefits from SAC by pointing out the problems arising from the US operation. Specifically, it supports detecting which cities are confronting which issues and why.

Selecting the proper dataset, integrating data sources into SAC, cleaning data, performing data through various graphs, and questioning and analysing data are all stages of the stimulation process to describe Fond Rouge using SAC to support them in business operations.

Based on the created model and stories in SAC, we can conclude that Fond Rouge are struggling with two problems: counterfeit in Los Angeles and Las Vegas and inferior products in San Diego. Thanks to quick identification, Fond Rouge can narrow the affected scope and minimize the damages in time with optimal solutions.

Although SAC also provides the schedule settings functionality to update data for models and stories from the newer versions of Fond Rouge's spreadsheets, live data in real-time can reflect the actual situation and support the decision-making process more precisely. Moreover, predictive planning is also one of the outstanding functionalities. But there is no chance to apply those functions to the case company in this report.

In conclusion, there is no denying that SAC supported the case company - Fond Rouge solving their daily activities and improving the decision-making process. Meanwhile, this research emphasizes three out of four functionalities of SAC by going through a whole process of using SAC to visualize and detect problems of the case company. There are Business Intelligence, Augmented Analytics, and Analytics Designers.

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