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The Expanding Role of Analytics in Operations

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Abstract

In the competitive business world today, every company must keep up with technological advances and, therefore, incorporate data analytics into their operations. Data analytics are a vital aspect of every department in every company. When these analytics are operationalized, or the analytics are automated and applied to the operational side, companies can increase productivity, efficiencies, and customer satisfaction. Through my thesis, I establish how utilization of operational analytics can provide a competitive advantage for a company. I walk through the history of analytics, the different platforms involved in making an analytics process operational, as well as the decisions involved. Along with secondary research, I have interviewed different analytics professionals, gained a certification in Tableau, a data visualization platform, and taken a course to learn the basics of the coding language, Python. The operationalization of data analytics is a unique subject that will grow in importance as the digital world develops.

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Introduction

In the competitive business world today, every company must keep up with technological advances and therefore utilize data strategically to gain information. Data analytics can and should be incorporated into every department of every company. Yet, specifically within the operations department, complex analysis of multiple data sources can result in an improvement of productivity and efficiency, and therefore profitability. Operational data analytics can provide a competitive advantage for a business if the development of information and automation systems is executed properly, and technology is frequently updated. While many people are not comfortable turning over day to day decisions to machines, augmented decision support systems are important to keep up with competitors and decrease uncertainty. There are hundreds of factors that must be considered when incorporating operational data analytics. Decisions regarding whether to incorporate operational data analytics include available technological platforms, skill, and costs behind specific additions. While it can be costly process, there are many benefits behind operationalizing data analytics.

Bongsug defines supply chain analytics as “a combination of multiple IT-enabled resources for manufacturing-related data management, supply chain planning and data-driven process and quality improvement”. He argues that IT and data cannot create value on its own, but it must be used in conjunction with a value creating process. When data analytics is combined with operational processes, it often removes the tedious day to day tasks which in turn helps inform bigger decisions made by a company. While many analytics are descriptive or predictive, operational analytics takes these analytics a step further and becomes prescriptive. It utilizes both descriptive and predictive analytics to automatically decide how to move forward. Prescriptive analytics allow the operations of a company to be proactive rather than reactive, meaning that problems are avoided overall by preventing them from happening or, if they do happen, the company knows exactly how to address the problem quickly and automatically. For these prescriptive analytics to be successful, a strong analytics foundation must be intact. A company must first decide that there is an aspect of their operations that can or should be improved then determine whether an investment into operational analytics can provide an efficient return. An organization must have the required skills and specifically the data to execute the operational analytics process. Additionally, they will need a team to design, build, and configure the process, then monitor that process over time. If successful, a company can develop a competitive advantage through improving efficiency, quality, flexibility, and even the customer experience.

Many corporations have utilized operational analytics to improve different aspects of their operations and therefore create a competitive advantage. Walt Disney Company developed ‘MagicBands’ for Disney World visitors to improve the customer experience and easily gather data. MagicBands are bracelets with RFID sensors used to enter the park and rides with the ability to associate with a credit card so customers do not have to carry one separately. With the data from these MagicBands, Walt Disney Company can see traffic patterns as well as each visitor's unique behavior such as where they are spending their time and how many rides they go on per day. Disney can inform customers of rides and restaurants with short wait times or upcoming events. Additionally, these MagicBands provide employees with name and age information of each visitor. This enhances the customer experience as a young child would feel more special if a character knew them by name. While this does affect the customer experience, access to data of each visitor in Disney World affects Walt Disney Company's ability to improve the park and therefore increase profitability. Disney can better distribute traffic patterns, and with shorter wait times, people are more incentivized to spend time at shops and restaurants and therefore spend more money (Franks 63). With more money spent and traffic better distributed, Disney is able to offer their guests more Fast Passes or access to the front of ride waiting lines. In turn, more guests will be attracted to attend Disney World due to their ability to get onto rides quickly and awareness of occurring events. Analytics help automatically determine what special offers to give each guest based on their unique behavior. Walt Disney's use of MagicBands is a perfect example of how operationalizing data analytics can enhance the customer experience and therefore increase profitability.

While Disney utilized operational analytics to enhance the customer experience, other industries often use analytics processes to improve operational efficiency. For example, GE Energy developed an operational analytics process for their wind turbines to respond to the variability in wind. The blades of the wind turbines will adjust their positioning and angle automatically through sensors tracking this information at a high level of detail. Efficiency is constantly maximized as fuel is saved based on this data. While this process only yielded a percent or two in additional output, this translates to millions of dollars saved each year for GE. Similarly, train companies use operational analytics to determine the efficient speed for each train to go based on upcoming traffic. With the proper speed, each train will arrive at every stop on time with minimal fuel used on accelerating and braking. Dr. Michael Gorman, a professor at the University of Dayton with experience in the rail industry, explained in an interview how analytics were used in his previous position. While dealing with train congestion was a major aspect of his job, he also used analytics to determine which car of each train should go to each customer based on the number of cars available, their location, and expected timing. Dr. Gorman developed an optimization model to solve this problem yet stated that there were many limitations due to a lack of technology during his work in the 1990s. He continues to occasionally consult rail companies on solving analytics problems and addressed that there are much higher capabilities now than in the past due to an increase in technology. There are thousands of different ways a company can use operational analytics to improve operational efficiency.

Another example of how companies utilize operational analytics processes is through the implementation of predictive maintenance. As stated previously, operationalizing these processes often allows a company to be proactive rather than reactive. Franks defines predictive maintenance as "the practice of using analytics to identify maintenance issues before they happen and to proactively address problems before failure occurs". Predictive maintenance uses past performance data to better estimate maintenance schedules in conjunction with the Internet of Things providing sensor data. The development of the Internet of Things, or a constant communication between the billions of devices around the world, has played a major role in providing companies with the opportunity to increase their analytics use. Machine failure and maintenance can take away time resulting in production loss and unplanned downtime, especially for companies with a heavy reliance on robots and automated machines. With utilization of sensor data, system component data is continuously evaluated until red flags are found and maintenance can occur prior to breakdown (Cio Techie). These red flags are often called early warning indicators, showing adverse system conditions such as friction build up or temperature increases. The ability to predict breakdowns is a major advancement for operations departments and can have a significant impact on the costs incurred. Predictive maintenance can lower manufacturer costs, improve safety, and even improve the service level. While there can be a hefty set up cost for these operational analytics processes, the returns typically exceed the cost depending on the size of the organization. Manufacturing companies typically reap the greatest benefits after incorporating predictive maintenance and improving efficiencies with operational analytics processes.

History of Operational Analytics

An important aspect of the history behind operational analytics is the idea that every concept built on one another rather than replaced. In developing knowledge of analytics, it is important to start from the beginning similar to how analytics professionals have done in the past. Many people are familiar with the idea of traditional analytics or coming to conclusions by simply studying or summarizing data. Traditional analytics utilizes descriptive statistics and reporting with a bit of predictive analytics. Traditional analytics began to be heavily used at the same time as technology began to develop. At this time, data was exclusively internally sourced and, as a result, well structured. More time was spent gathering the data than analyzing it. The lack of platforms supporting this resulted in a significant amount of time taken to prepare the data in addition to gathering it. Analytics became even more complicated when the Internet and Big Data began to develop.

The next era of analytics, known as the Big Data Era, truly exploded the field of data analytics. The Internet and new software provided a connection to millions of different sources for data. Franks defines every industry's focus during this era as "to find the cheapest way to collect and store data in its raw format and then worrying later about figuring out how to make use of it" (13). With a variety of sources, a variation in data formats provided a significant challenge and financial investment to companies looking to utilize analytics. The cost involved with analytics skyrocketed as it was difficult to efficiently work with complex, large, and unstructured data with little resources. Additionally, new information and increasing level of detail is what makes big data so powerful but also challenging as more data required updating more frequently and therefore more of a time investment by companies. With new analytical and computational capabilities, the term data scientist began to surface. Analytics professionals began to have direct influence on a company's executive decisions as it was a new approach to decision making. The Big Data era focused on dealing with large amounts of complex and unstructured data and incorporating analytics professionals into corporate teams.

To understand operational analytics, it is vital to know where the analytics have come from. By understanding the techniques utilized in the traditional analytics era and big data era, it is much easier to understand how they come together to form the era of 'unified analytics'. As the variety and novelty of data sources evolved, new technology and data innovations continued to advance and operational analytics became possible. Once more advanced platforms were developed to support big data, the next key step is to integrate all these platforms in one environment, allowing the data and algorithms to work together automatically. Allowing this integration can provide a major increase in efficiency and less time spent on rudimentary day-to-day decisions. Therefore, more time and money can be invested into discovering new analytics and improving the operational analytics processes. A key aspect of the 'unified analytics' era is the development of the idea of discovery. With an increase in professionals within analytics, people began to spend their time looking for new questions and relationships without a prior indication that it existed or was relevant. New technological platforms have been developed to support the discovery process. The idea of exploratory data analytics helps to explain the process to approaching discovery and turning intuitions into models. Exploratory data analytics and discovery platforms will be further discussed throughout the paper. Understanding the relationship between descriptive and predictive analytics helps an analytics professional develop operational analytics processes with the utilization of prescriptive analytics.

Platforms for Incorporating Operational Analytics

Operational analytics work at the intersection of three different technological platforms. The relational, nonrelational, and discovery platforms each offer their own purpose and are equally fundamental to ensuring a functional and flexible operational analytics process. A relational database ultimately embeds the data and algorithms developed in the nonrelational and discovery platforms with the operational processes. A nonrelational platform, often Hadoop, can be the initial storage location for all data. The discovery platform allows professionals to develop new analytics and test those data relationships. There are many more functionalities involved within each of these platforms.

The relational database takes the analytics developed in the discovery process and ultimately incorporates this with the operational process. This database is often established prior to the operational analytics development as it manages data that supports the enterprise applications. Relational databases utilize tables to store data, providing an efficient and flexible way to generate intuitive reports for analytics. The coding language, SQL (Structured Query Language) is used within this database to query this data and apply those queries across different platforms. With the ability to store common querying procedures, applying queries hundreds of times to different data can be done within seconds. Which features to incorporate into the relational database in conjunction with cost concerns should be determined on a company-by-company basis.

Developing an efficient relational database with proper flexibility and scalability is key in creating a working operational analytics process. Having a resource management subsystem allows many different users and processes to access the information simultaneously while tightly controlling who can access specific data with sophisticated security capabilities. Gartner Information Technology defines scalability as "the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands". Having a proper level of scalability will reflect the processing power and data volume, while allowing for large batch processes and querying. The ability to process data in parallel will provide extra scalability. There are hundreds of different formats that data can be stored in. A system with extra flexibility can speed up the process of utilizing semi-structured data such as JSON and XML, data that does not use the row and column format that relational databases assume by default. With a recent burst in cloud-based platform use, it can be easy to access changing data across many different platforms, often interconnected by an enterprise resource planning system.

Relational databases are the "scalable backbone of an organization when it comes to making analytics operational" (Franks). When deciding on a relational database that is right for a certain organization, there are many different factors to consider. One would be determining the correct level of scalability with a consideration for expected growth in a company. Another is concurrency and determining how many processes and users will be working within the platform simultaneously. If the data is not frequently perfectly structured, a company should find a platform that allows for flexibility when working with this data. If it is a large organization, security must be strongly considered as every user should not have access to all data. A cloud-based system is required for large organizations utilizing a variety of data sources for there to be consistent updates to the data. Constantly having updated data is a requirement for operationalizing a process as it cannot respond accordingly without this new data. While one may think having the best of all these factors in a relational database is the answer, it can be expensive and must be considered with a budget. Yet, not having enough of any of these factors can result in lost time and therefore money wasted. Developing a solid relational platform is essential to creating an efficient operational analytics process.

The second platform used in operationalizing data analytics is a nonrelational platform. It is valuable for “the staging and initial processing of all types of data since it makes no assumptions about data structure” (Franks 126). The nonrelational platform is vital as all data gathered is stored here without concerns for hanging onto low-value data that could one day be useful. Hadoop is frequently used for this platform as it is open-sourced, meaning programming previously developed by another company or individual and can be used by anyone, and it therefore does not have a licensing fee. Hundreds of different programming languages including SQL and Python are used within this platform and there is not a required data format. This means that it is possible to “load text, photos, videos, images, log data, sensor data, or any other type of data exactly as it comes in and then process it in parallel” (Franks). A large file is broken down into bits and pieces and, once processed in parallel, it can be easily extracted to an analytics process (Gupta). If the relational database is incapable of processing data without a required format or structure, it is often done within the nonrelational platform. Many companies decide to have a more flexible relational platform since Hadoop can be slow and more difficult to work with. To maximize Hadoop’s capabilities, it should be added to an existing environment rather than replacing it.

Despite Hadoop’s many capabilities, a relational database is still required to perform operational analytics processes. It is required to combine this data with the operational process, which will then react to the data it is fed with proper machine-learning algorithms. With a combination of the two, Hadoop has an Enterprise Data Hub (EDH) that “can integrate all enterprise data sources . . . and make that data available with EDWs for advanced analytics on manufacturing industrial data to gain valuable insights on subject areas such as product, process, customer, inventory and supply chain.” (Gupta). If a real-time data monitoring platform is integrated, Hadoop can provide live access to this data, including data from the Internet of Things (IoT). This allows machine logs and sensor data to be consistently updated, along with a performance history stored in Hadoop. By carefully crafting the Hadoop EDH, each source utilized will be separate subject areas, then broken down into pieces for each subject. By leveraging machine-learning algorithms, connectors and APIs available as purchasable additions in Hadoop in conjunction with statistical techniques, Hadoop's EDH can provide reports as well as a forecast for "production, supply, customer satisfaction and infrastructure durability" and "raise risk flags in advance" (Gupta). For companies with a wide variety of databases, Hadoop EDH can be used to bring the data together with a multitude of intuitive benefits.

When building an operational analytics process, there are a lot of questions involved that have not been previously answered. The discovery platform is how analysts, programmers, and data scientists go about finding the solution for these questions. It involves the "mixing and matching of all kinds of data. . . with limited rules and constraints" (Franks 130). Many analytics processes are tested here before being executed on the relational database and process itself. While in the past this platform was separated from the others, it is now recommended to be integrated so the platform can be scalable and easily access outside data. For companies who may be looking to integrate very few processes and already know the detailed logic on how to incorporate the analytics, this platform would not be needed. If the chosen discovery platform does not have the ability to streamline a code into another platform, the code would need to be repeated elsewhere.

Typically, general management will be looking to develop an operational analytics process without any prior knowledge on how to make this happen. Common platforms do not typically have the freedom to "to recast data, change layouts, and experiment" like platforms specifically developed for discovery. For companies that utilize operational analytics there is always an expectation to operationalize another process in the future. In this case, it is important to have this platform readily available and easy to work with. It is essential that the discovery platform is flexible and user friendly so new insights can be found faster. Additionally, this platform should support relational and nonrelational processing, including text, graph, geospatial, and other analytics rather than traditional statistics and forecasting methods. Through this platform, data scientists will create their own algorithms and utilize SAS, SPSS, R, and other coding languages. If the chosen discovery platform does not have the ability to streamline a code into another platform, the code would need to be repeated elsewhere, requiring extra effort. The time to find insights should always be more relevant for this environment than performance or scalability, as time can incur more costs than either of these factors. This is where the idea of Exploratory Data Analytics is executed, an extremely relevant mental process in discovering how to make an analytics process operational.

Exploratory Data Analytics

In the 1970s, John Tukey developed a thought process to analyzing data known as Exploratory Data Analysis (EDA). He places a focus on the discovery of structures and patterns in the data with a flexible mindset to inform modeling decisions. The discovery process through EDA allows an analyst to find the questions that can be addressed through analytics and ultimately incorporated into operational analytics. The discovery process can help to discover other relevant variables that were not previously considered and establish the need to collect this data or wrangle the existing data further. A common term used within analytics is data profiling. Profiling involves fixed questions and datasets beforehand, making it much simpler than discovery. Tukey's exploratory data analysis can be applied to any analytics in addition to operationalizing an analytics process.

John Tukey developed five steps to data analysis including acquisition, wrangling, exploration, modeling, and reporting (Wongsuphasawa). Acquisition deals solely with finding the data and potentially gathering the data yourself. Only 5 out of 18 analysts in Wongsuphasawa's study claimed that they participated in data collection. Data wrangling involves dealing with this data and its size, format, and erroneous values. Too large of a data size can increase processing time and even crash the analytics tool. To control data size, the data can be sampled if it is 'meaningful and representative'. The data can also be aggregated once the correct level of detail is determined. As discussed previously, data formats are difficult to work with and it requires a very flexible platform to work with these different formats. Data wrangling includes converting data formats to be parallel. All values should be analyzed to determine any outliers or erroneous values that may throw off analysis. 'Domain knowledge' is used in this instance as it is important to have the expertise on the data before making changes that could produce improper results. Once data wrangling is finished, exploration begins by brainstorming the meaning behind the data.

The exploration stage of exploratory data analysis can be the most time consuming but also the most valuable. While Gartner developed the three Vs about data, volume, variety, and velocity, Franks adds another important V, which is value. Once the value behind the data exists, there are many different decisions regarding what aspects to explore. Sometimes, there are hundreds of different variables and many can be correlated but not important. To narrow down the variables, many analysts "drew diagrams between variables with potential relationships" to decide which variables are relevant (Wongsuphasawa). Another decision is whether to focus on direct data, summary statistics, or univariate distributions like histograms and count plots. A key question asked in Wongsuphasawa's interview study that I also asked the different analysts I interviewed is 'When does exploration end?'. Every single analyst from the interview study stated that it was at the time of goal satisfaction, or when they had answers on how to answer the questions or formulate a model. Half of the analysts said that a time constraint often ended their exploration and they had to continue to begin modeling with questions unanswered. A few analysts indicated that feedback from stakeholders would give them the indication that they can continue to modeling. Once exploration is finished, it can be easy for analysts to test their hypotheses and know how they should model their findings.

The final steps of data analysis are modeling and reporting. In my interview with Tyler Deutsch, a P&G data scientist in advertising, he broke down modeling into three key steps. After developing a hypothesis such as a prediction of sales, he would input the variables into the proposed model. From there, he utilizes algorithm toolboxes, such as Python, to run those variables and determine if there is statistical significance. While Tyler typically uses Python for model development and running predictions, there are other tools utilized as well. He uses Microsoft Azure to store data and compute nodes for processing and running models. SQL is used for coding and querying purposes. Within my interview with Jacob Loeffelholz from aerospace company The Perduco Group, he claimed to use many of these same tools. Loeffelholz takes analytics a step further as the operationalization of analytics is the product itself that is sold to the public. He uses R since it allows a prototype to be executed on any website, as well as Jump and SAS for easy reporting.

Reporting can be difficult as you typically must shape the report to the audience it is provided for. Sometimes multiple reports will have to be developed to fit the needs of different clients. To learn more about reporting, I took an eight-week course on Tableau, a data visualization platform. Tableau takes the data from a database or spreadsheet and provides hundreds of different ways to present this data. Ironically, Tableau sells operational analytics as their product. The platform allows each report to have a live connection, meaning that every time the data source is updated the reports will automatically be updated as well. I have found Tableau to be a quick and easy to use platform for reporting data and I plan to utilize it in the future. Tableau makes it easy to report data so more time can be spent in exploration.

There are many challenges faced by analysts when executing EDA. One of the most frequent complaints made is about repetitive tasks. Specifically, they spend a lot of time recreating the same methods and algorithms for each different variable. In my interview with Tyler Deutsch, he said he wished there were a way for updates to datasets to be make automatic. He currently solves this problem by being quick to make incremental improvements and updates. With proper operational analytics processes, he believes this problem will be solved in the future. Another problem addressed is the rarity of having a clean dataset. Having different sources and granularities of the data can slow down the analysis process significantly unless a company invests significantly in adding flexibility to a platform.

If it were always clear what the question being analyzed was, as well as what algorithm/approach to use while analyzing this data, data analytics would be simple. Yet, the ambiguity behind these concepts is what makes analytics as challenging as it is, especially when determining how to invest in operational analytics. Wongsuphasawa addresses that there are solutions to speed up the analytics process, specifically within the design of the program being used. There are ways to automate the repetitive tasks described above as well as exploration tools to help with data wrangling and deciding on variables. Jacob Loeffelholz expressed that many of his clients will want a certain result and it is a challenge for him to not manipulate the data to the point that it is inaccurate. The interview study shows that analysts face a similar problem avoiding bias from stakeholders. Data analysts must have the objective of producing accurate results in an efficient time frame with a consideration for all these challenges. Ethical challenges associated with data analytics must be acknowledged and properly resolved.

Creating a Plan for Operational Analytics

Franks defines a successful operational analytics process as "putting the data, tools, and technology in the right context". There is a lot of research and decisions required when deciding where to execute operational analytics, and ultimately whether the investment will pay off. Incorporating new information should always be prioritized over investing in a new process with old information. With ample amounts of data available, it is important to begin with a question or target measure to change. Discovery is heavily used in operationalizing analytics processes rather than other analytics because the path to and definition behind success is unknown. Discovery begins with a broad goal or set of hypotheses without the ability to set any predictions of time or effort required. Especially within operationalizing an analytics process, analytics teams will try different discovery processes simultaneously until one works out. It is also challenging to decide when success is reached and ready to be implemented. Once the discovery process is deemed to be complete, the analytics team will run a confirmatory analysis to ensure that their results are valid.

When deciding on platforms to utilize for the analytics process, it is important to have the proper level of scalability and flexibility as well as a cloud-based system to gather data from and integrate into the developed system. Many different applications are involved or integrated within one analytics process. While it may be easy to choose a tool once it is determined to be functional, it must also be considered how well the tool can be integrated with the operational environment. At times, there is more importance on a tool's ability to handle hundreds or thousands of analytics decisions at once than other considerations such as user-friendliness (Franks). Sometimes putting less of an emphasis on sophistication and accuracy and moving forward to test the results can lead to a better time investment. Instead of spending time on each individual decision within an analytics process, Franks recommends making the goal to "to maximize the aggregate impact of the process across all decisions" (197). Like a new product in the R&D stage, every operational analytics process will be tested on a small scale first as a prototype before execution on the operational environment to account for errors beforehand.

The cost behind operationalizing the analytics process is and should be a major consideration while making decisions. The company should consider their expected returns with a successful analytics process rather than simply the costs of making it happen. Operationalizing an analytics process is a long-term investment and typically requires an analytics team to keep up with the process and make incremental improvements. When deciding whether to invest in an operational analytics process, the executive team should determine what the ultimate benefit of having this analysis would be, as well as the effectiveness of the different options for executing that analysis. The value behind the analytics lies in how efficiently the team can create, test, and execute the operationalized process (Franks). Time to insight reflects the amount of time taken from when the data is acquired to when insights have been found. A shorter time to insight will provide higher returns as extra labor costs typically exceed the costs of extra processing time. The sooner an insight is found, the sooner the analytics team can move onto the next discovery process. Entering the discovery process with specific questions can help to speed up the time to insight. Choosing the right questions to ask can increase the value more than the details within the creation process.

Many companies utilize the total cost of data framework (TCOD) to determine the costs associated with an analytics process. Costs included with TCOD include "Hardware, software acquisition, space used, power consumed, labor costs, data preparation and acquisition, test code logic, maintenance costs, [and] training for staff" (Franks 102). Scalability is also a relevant cost as it dictates how many processes and tools can be integrated, how many users can utilize the system at once or the concurrency, and even security. As an example of cost consideration, some companies may choose to operationalize analytics processes as it may increase the utilization of existing capacity and therefore eliminate the need to build new plants. In this case, the costs of building a new plant would be compared with the costs of operationalizing an analytics process, with a consideration for differences in capacity. Much like building a new plant, operationalizing an analytics process is a long-term investment. A company is more likely to have greater returns if they target differentiators or unique factors that can set their product or process apart rather than simply making incremental improvements. While many companies will try to reduce costs as much as possible, sometimes the more expensive option can provide a greater return on the investment as well as potentially make it easier in the future to consistently update the process. If a more expensive option is chosen, the costs and benefits should be analyzed in comparison to other alternatives to have a solid understanding behind why that route is necessary.

There are many considerations an executive team should have in mind when deciding whether to operationalize an analytics process as well as where this process should be applied. First, what the team is looking to maximize or minimize should be determined. Second, they should consider the effects of accomplishing this on labor and process efficiency. For example, adopting an operational analytics process will sometimes reduce the need for human capital or allow the analytics team to perform their duties faster or more efficiently. The expected time to insight should be compared between the different options in addition to the costs of the technology. Other considerations include the company's willingness to experiment, support change, or decrease the time to insight. In terms of where the analytics should be executed, the team should investigate whether the environment can handle the processing and whether the team has the tools and skills to execute the analytics process. These are a few of the questions that any company should consider before diving into building an operational analytics process.

As technology continues to develop, there will constantly be improvements to analytics and new developments within operational analytics processes. It is important for a company who invests in operational analytics processes to keep up with these improvements to maintain the competitive advantage provided. It is important for a company to spend time determining the proper platforms to utilize as well as features to incorporate. Determining the proper levels of scalability and flexibility can be crucial to a successful operational analytics process. Another important aspect in executing these processes is ensuring that the analytics professionals have the skillsets to do so efficiently and effectively. A good analytics professional has a grasp on the history of analytics and the process behind exploratory data analytics. Additionally, this professional must have the creativity to execute the discovery process if the question is not clear from the beginning. Operational analytics processes are vital in many industries today to keep up with competitors by improving productivity, efficiencies, quality, customer service, and therefore profitability.

Personal Reflection

As a future analytics professional, I look forward to applying this array of knowledge on analytics in conjunction with my Operations and Supply Management degree in my future career. Developing my comprehension of exploratory data analytics has helped me understand the process behind developing and executing a model for analytics as well as the importance of spending time within the discovery process to ensure there is not a better outcome. As a business economics major, I developed a research study this semester and gained the experience of applying the exploratory data analysis method to analyze my personally gathered data and ultimately find the perfect model. Additionally, the opportunity to work with different data within Tableau has taught me the endless interpretations of and meanings behind every piece of data. In addition to learning the analysis process, I hope to influence companies that I encounter with my knowledge on the possibilities surrounding operationalizing analytics processes. While it may be a relatively new subject, at one point in the future I predict that multiple analytics processes will be embedded in every company's operations. As I venture into a career, I plan to continue growing my knowledge on analytics in operations and to keep up with new advancements the world of analytics will uncover.

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