Fostering Business Analytics Success: Examining Leadership Support, Data Quality, and User Skills in Philippine Manufacturing Companies

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ABSTRACT

Manufacturing organizations have seen business analytics improve employee performance, cost savings, and operations to expand and succeed. This study analyzes how data quality, user skills, and leadership support affect manufacturing business analytics. It provides a comprehensive framework that assesses the interrelationships and effects of these critical components and improves manufacturing data quality. Five Philippine manufacturing companies with at least 10 years of experience and similar workforce counts were selected. Automatic random selection recruited 80 persons from each group, totaling 401. The structural equation modeling and multiple regression analysis reveal that data quality, user skills, and leadership support significantly affect business analytics success. Data quality boosts analytics efforts by exposing the requirement for accurate, complete, and relevant data. Users with technical, statistical, and analytical capabilities benefit from analytics solutions, stressing the necessity for a competent workforce. Leadership support is the most significant predictor, showing the relevance of organizational leadership in business analytics effectiveness. Resource allocation, collaboration, communication, and staff development substantially impact analytics initiatives. Business analytics performance depends on data quality, user capabilities, and leadership support. It delivers manufacturers actionable data to strategically improve operational framework components to improve analytics outcomes.

Keywords: Business analytics success, leadership support, data quality, manufacturing.

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1. INTRODUCTION

In today's manufacturing landscape, business analytics is seen as a game changer that can reshape norms. Also, it paves the way for business growth, more so in the Philippines, where the industry is the third-largest contributor to gross domestic product (GDP) growth (Department of Trade and Industry, 2023).

Manufacturing companies increasingly leverage analytics to drive business outcomes, enhance decision-making, and improve efficiency. The rising prominence of technology and the explosion of data underscore the importance of this trend. As such, there is a growing recognition within the manufacturing industry of the power of analytics. In

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response to this realization, businesses in this field heavily invest in building capabilities and expertise.

However, while analytics has garnered acclaim, its impact hinges on crucial factors that must be carefully considered. User proficiency, data quality, and support from leadership stand out as elements in maximizing the benefits of analytics within manufacturing operations. Combining these components forms the foundation for applying analytics in the manufacturing sector.

These factors impact how well these efforts work and influence the company's performance. The trustworthiness and accuracy of the discoveries are directly affected by how precise, thorough, and relevant the data is. Therefore, ensuring data integrity plays a role in any project involving analytics. When considering the manufacturing sector, which generates amounts of data through operational processes, it becomes crucial to prioritize maintaining data integrity to uncover valuable insights that aid in making informed decisions.

Furthermore, it is equally essential for users to be adept at utilizing analytics tools and interpreting analysis outcomes. The level of user proficiency across domains like understanding reports, technical expertise, and analytical skills determines how effectively analytics can extract meaningful insights and enhance measurable business outcomes. This is because analytics empowers users to derive insights and drive business growth. It's essential to have advanced solutions to tackle operational hurdles commonly found in the manufacturing sector.

Thus, the workforce's expertise plays a role in determining the success of analytics projects, support from leadership is vital for all project endeavors in business analytics. It is equally crucial as user capabilities and data quality. Cultivating a culture that values data-driven decision-making promotes analytics usage in project pursuits. Allocating resources to support these efforts falls under the responsibility of leaders with significant influence in these areas. Several key factors in manufacturing contribute to integrating and deploying analytics, such as fostering collaboration, embracing innovation, and having strategic foresight.

Given the context, this study aims to explore the factors influencing the success of business analytics within the economy's manufacturing sector. It explores how data quality, user expertise levels, and various leadership roles interact. The main goal of this study is to create a framework that explains how certain vital factors impact the results of business analytics implementation. In a business environment, the study aims to offer manufacturing companies valuable insights that they can use to enhance their analytics initiatives and promote sustainable growth. By extension, this paper also contributes to the field of management in general, as the findings will validate how the resource-based view (RBV) applies in the context of business analytics. Also, since leadership concepts are relevant and essential across different types of organizations, the findings can benefit industries beyond manufacturing.

2. LITERATURE REVIEW AND FRAMEWORK DEVELOPMENT

Recent research highlights the transformational power of business analytics (BA) in improving organizational performance and competitiveness, notably in the manufacturing

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sector. BA has been demonstrated to favorably impact Six Sigma practices, organizational creativity, quality performance, and business performance in industrial environments (Maia *et al*., 2024; Geary and Cosgrove, 2023; Kristoffersen *et al*., 2021; Cao *et al*., 2021). Its continuous utilization, especially big data analytics, is becoming more relevant to improving operational performance in the manufacturing sector (Abdian *et al*., 2021; Kamble *et al*., 2020; Belhadi *et al*., 2019; Omar *et al*., 2019).

The literature on enhancing performance and productivity in manufacturing provides more insights into the multidimensional nature of organizational success in this industry. Kareska (2023) highlights the need to take a comprehensive approach to increasing productivity, which includes leadership, technology adoption, labor management, and corporate culture. Almazyed *et al*. (2016) stress the vital significance of dedication and work performance in boosting productivity, emphasizing the need to promote employee engagement via professional development and recognition activities. Furthermore, Shi *et al*. (2020), Abdelwhab Ali *et al*. (2019), and Kamble *et al*. (2020) investigate lean manufacturing practices, knowledge-sharing strategies, and smart manufacturing performance measurement systems, all to increase productivity and performance in manufacturing organizations. These studies underline the necessity of implementing creative methods, cultivating a culture of continuous improvement and learning, and utilizing technology breakthroughs to increase productivity and competitiveness.

Data Quality

Ensuring high-quality data is essential for implementing business analytics in manufacturing operations, where accurate and reliable data is vital for informed decision-making processes. This is especially crucial within the domain. Data quality encompasses three elements: accuracy, completeness, and relevance (Ferreira *et al*., 2024). By utilizing data sets in manufacturing analytics applications, values can be accurately represented to provide a reliable foundation for decision-making purposes.

The effectiveness of business analytics initiatives in manufacturing greatly depends on data quality. Utilizing high-quality data guarantees the acquisition of comprehensive and relevant insights from processes. This enables decision-making based on information and drives efficiency enhancements. Wang and Hsu (2021) stress the importance of using comprehensive data for demand planning and sales forecasting in manufacturing operations. The study highlights that making uninformed decisions can lead to inventory imbalances, production inefficiencies, and missed income opportunities due to insufficient data.

Data quality is a crucial factor that significantly impacts the effectiveness of business analytics initiatives. It plays a significant role in defining the decision-making procedures, operational effectiveness, and overall performance of organizations. The link between data accuracy and important success variables in organizations needs dependable data management techniques and the promotion of third-party systems to enhance data dependability. Yu & Zuo (2022) investigate the engineering industry to see how innovative approaches might improve data precision. Furthermore, the study conducted by Zeleke *et al*. (2021) examines the effects of surveyor-administered computerized data-collecting techniques on data accuracy in Population and Health Surveys (PLS). The research emphasizes the benefits of electronic data-gathering systems compared to conventional paper-based approaches, emphasizing their effectiveness and ability to

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avoid errors in real-time. The results emphasize the significant impact of data correctness on cost-effectiveness and the need to implement robust methods to ensure data quality assurance.

Wang *et al*. (2022) investigate the application of big data analytics to intelligent manufacturing systems. While not explicitly addressing business analytics, their study underscores the broader implications of accurate data and how analytics enhances operational efficiency and productivity across multiple industries. Raman *et al*. (2018) describe the effects of data precision on supply chain management. Their exhaustive investigation, which incorporated specialists from numerous regions and industries, sheds light on how data precision impacts supply chain metrics such as vendor evaluation, operational effectiveness, and demand management. Furthermore, Shahid and Sheikh (2021) investigate the impact of big data on innovation, competitive advantage, and decision-making. While the study does not center on data quality, it does demonstrate the potential of precise data to facilitate organizational success. According to the guidance provided by industry specialists and decision-makers, the researchers emphasize the strategic significance of utilizing precise data to make informed decisions and attain a competitive advantage in dynamic business environments.

These studies highlight the significant impact that data quality has on the effectiveness of business analytics when used together. The relevance of this argument is that firms must emphasize data integrity as an essential component of their analytics initiatives. With organizations increasingly relying on data-driven insights for strategy development and decision-making, data veracity must be recognized as crucial in establishing long-term competitive advantage and organizational success. Thus, this study hypothesizes that:

> *H1: The completeness, accuracy, and relevance of data, collectively termed data quality, significantly influence business analytics success in manufacturing companies.*

User Skills

The skill of business analytics users is a significant factor in determining the level of success that manufacturing businesses achieve in BA implementation (Su, *et al*., 2022). The technical proficiencies, statistical acumen, and analytical aptitudes of users are dimensions to be considered. Having technical capabilities entails understanding business analytics software tools in addition to having competence in the procedures of data extraction, transformation, and encoding. When analyzing production data and extracting practical insights using various statistical methodologies, having a solid command of statistics is necessary. Problem-solving, pattern detection, and the ability to critically evaluate the quality and significance of data are skills that are included in analytical abilities.

Proficiency in technical aspects is essential for effectively utilizing business analytics tools and platforms to derive practical insights from intricate datasets. Maia *et al*. (2024) underscore the significance of user proficiency in operating business analytics software and tools. They specify that technical competence empowers users to efficiently navigate data sources and perform analytical tasks. Moreover, according to Abdian *et al*. (2021), individuals possessing sophisticated technical abilities are more capable of investigating novel data-driven solutions and exploiting developing patterns in BA research. This, in

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turn, increases the likelihood of value generation and competitive edge in the manufacturing sector.

A thorough understanding of statistical methodologies and principles is critical to accurately interpret analytical results and arrive at well-informed decisions grounded in data-driven insights. Cao *et al*. (2021) provide evidence that individuals possessing statistical expertise exhibit more proficiency in performing rigorous analyses and discerning significant patterns within datasets, resulting in enhanced environmental monitoring and innovation outcomes. Furthermore, Omar *et al*. (2019) posit that individuals possessing proficiency in statistics are more capable of discerning the underlying factors contributing to quality problems and executing focused interventions to optimize processes.

Analytical skills comprise the capacity to assess data critically, generate hypotheses, and extract actionable insights that influence business results. Kristoffersen *et al*. (2021) emphasize the significance of analytical capabilities in resource orchestration and circular economy implementation, arguing that individuals possessing robust analytical abilities are more adept at recognizing prospects for optimizing resources and implementing sustainable practices.

Users' expertise in technical, statistical, and analytical fields directly impacts the overall success of business analytics initiatives in multiple aspects. An investigation conducted by Geary and Cosgrove (2023) demonstrates how proficient users can exploit business analytics tools and operational data analytics to optimize manufacturing operations, decrease maintenance expenses, and augment overall business performance. In addition, the transformative potential of BA capabilities in enhancing manufacturing processes and facilitating agile, data-driven decision-making is emphasized by Belhadi *et al*. (2019) to rely mainly on user skills.

In summary, user skills, encompassing technical proficiency, statistical acumen, and analytical prowess, are pivotal factors that ascertain the success of business analytics endeavors within manufacturing establishments. Proficient users possess the necessary capabilities to effectively utilize BA tools and platforms, thereby stimulating enhancements in operational procedures, financial savings, amortization, employee output, and productivity. Thus, this study hypothesizes that:

> *H2: The technical expertise, statistical knowledge, and analytical prowess, collectively termed user skills, significantly influence business analytics success in manufacturing companies.*

Leadership Support

Leadership support is germane in cultivating a work environment that values data and supports implementing analytics projects within firms (Liu *et al*., 2021). Key focus areas for leadership support include allocating resources, promoting communication and collaboration, and investing in employee development. By allocating resources, manufacturing analytics teams can have the personnel, tools, and training to excel. By encouraging communication and collaboration, exchanging ideas throughout the organization can be better facilitated, fostering more teamwork. By investing in employee

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development initiatives such as training programs and study grants, learning and innovation in applying analytics to business strategies are promoted within manufacturing teams.

Sharma *et al*. (2022) emphasize the importance of management's dedication to leadership roles and timely provision of resources like time, funding, and skilled manpower to enhance plan implementation effectiveness. Similarly, Liu, *et al*. (2021) posit that leadership support is essential in budg*et al*location, in securing human resource commitments, and in offering training for analytics activities within manufacturing processes. After all, organizations supported by their management can leverage analytics for decision-making, leading to improved performance (Bag *et al*., 2021).

Leadership support is essential in nurturing a culture centered on teamwork, effective communication, and sharing information. In the realm of manufacturing businesses, having leadership support is crucial for the success of BA programs. How analytics initiatives are embraced and executed depends on leadership dedication, resource allocation, and company culture. According to a study by Ferreira *et al*. (2024), senior management plays a crucial role in manufacturing environments by spearheading transformation efforts and advocating for sustainability practices. They emphasize that proactive support from leaders is essential for fostering an environment that values innovation, collaboration, and continuous improvement. This sets the stage for companies to make informed decisions and enhance their performance through analytics. Moreover, Bag *et al*. (2021) explore how leadership support impacts supply chain resilience and competitiveness amid the challenges of COVID-19. They underline the importance of forward-thinking leadership, strategic planning, and involving stakeholders in navigating disruptions and building supply chains. Strong leader support increases the likelihood of success and longevity for data analysis projects by ensuring support, skilled personnel, and organizational alignment. The success of BA projects relies heavily on the efficient deployment of resources, which is crucially influenced by effective leadership. Raut *et al*. (2019) and Omar *et al*. (2019) have conducted studies that underscore the significance of allocating resources toward technological infrastructure, talent acquisition, and data management systems. Adequate allocation of resources to BA initiatives is facilitated by leadership support, which in turn enables the gathering, analysis, and application of insights into manufacturing processes. Strategic resource deployment allows firms to use BA effectively to enhance operational optimization and efficiency.

In business administration, leadership support encompasses facilitating workers' skills and competency development. The authors Ren *et al*. (2018) and Lazarova-Molnar *et al*. (2019) emphasize the importance of leadership in fostering a culture that encourages ongoing learning and the enhancement of skills. Through the deployment of training programs, seminars, and mentoring efforts, leaders facilitate the development of workers' analytical talents, statistical knowledge, and technical skills necessary for the successful execution of business analytics.

Leadership endorsement is crucial in fostering cooperation and communication channels favorable to business analysis's success. Leaders play a pivotal role in promoting the sharing of ideas and data-driven decision-making across departments by actively supporting open communication, dismantling organizational silos, and encouraging multidisciplinary cooperation. This cooperation and collaboration also shape an organization’s BA culture. Fosso Wamba *et al*. (2020) revealed that the business

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analytics culture within the organization mediates the effects of the enterprise's sensing capability on its business performance, mainly financial- and marketing-wise. Establishing effective communication channels to support the engagement, information dissemination, and alignment of essential stakeholders with business analysis goals facilitates simplified workflows, improved coordination, and expedited decision cycles.

The combination of leadership support in allocating resources, developing employees, fostering cooperation, and facilitating communication results in achieving BA success outcomes. Enhanced procedures arise from the efficient allocation of resources, simplified workflows, and evidence-based decision-making assisted by leadership endorsement. These benefits arise from improved operational efficiency, proactive problem-solving, and streamlined supply chain management, all driven by insights derived from business analytics (Raut *et al*., 2019). Leadership support is crucial in facilitating the performance of business analysts in manufacturing businesses. Leaders establish an atmosphere that promotes using business analytics (BA) to improve processes, reduce costs, save money, and boost employee performance and productivity. This is achieved by supporting efficient resource allocation, encouraging employee growth, and promoting cooperation and communication. By implementing strategic leadership initiatives, manufacturing businesses may use the transformational potential of business analytics to obtain a competitive advantage in the ever-changing business environment. Thus, this study hypothesizes that:

> *H3: Allocating resources, promoting communication and collaboration, and investing in employee development, collectively termed leadership support, significantly influence business analytics success in manufacturing companies.*

Leadership Support on Data Quality and User Skills

Establishing a company culture that prioritizes data integrity needs leadership support (Abdallah *et al*. 2020). Influential leaders invest resources, build frameworks, and explain expectations to support data quality projects. Leaders enable employees to maintain high data quality standards by providing enough resources and enforcing robust frameworks (Kim, 2020). Prioritizing data quality culture and resource allocation is critical to ensuring the dependability and credibility of company data.

Effective leadership encourages open communication about data quality criteria, standards, and best practices (Abdallah *et al*., 2020). In terms of data integrity, leaders ensure that people understand their separate roles and responsibilities (Kim, 2020). Furthermore, CEOs underline the importance of high-quality data in attaining organizational success via informed decision-making (Abdallah *et al*., 2020). When CEOs express trust in data-driven operations, employees are more inclined to emphasize data quality in their daily tasks. This leads to higher data quality and more efficient decision-making. Thus, this study hypothesizes that:

> *H4: Leadership support for business analytics initiatives significantly affects the data quality gathered and used in manufacturing companies.*

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H5: Data quality mediates the effects of leadership support on business analytics success in manufacturing companies.

Leadership support is crucial in shaping users' skills and expertise within the business analytics domain. Abdelwahed and Doghan (2023) stress the significance of leadership support for organizations to increase employee productivity and performance. An environment conducive to the growth and involvement of employees is fostered through leadership support, manifested through management involvement, provision of resources, and administration of positive reinforcement. This type of support strengthens overall performance and productivity by aligning individual abilities with the organization's goals. Saputra *et al*. (2023) emphasize the importance of leadership support in facilitating work performance by improving analytical tools and systems' perceived usability and benefits. The promotion of analytics platform adoption and utilization is facilitated by the active involvement of leadership, which empowers users to enhance their data-driven decision-making. This emphasizes leadership's critical role in promoting the deployment and integration of analytics initiatives into daily operations and supporting such endeavors. In addition, the significance of leadership in upholding data quality, which ultimately impacts user proficiency in business analytics, is underscored by Timmerman *et al*. (2023). Enhancing the reliability and validity of analytical outputs and bolstering user confidence and proficiency with analytics tools are objectives propelled by leadership in data quality assurance and management. In an increasingly data-centric business environment, adequate leadership support establishes the foundation for data-driven decision-making, enabling users to obtain pertinent insights and propel organizational triumph. Thus, this study hypothesizes that:

H6: Leadership support significantly affects the users' business analytics skills in manufacturing companies.

H7: User skills mediate the effects of leadership support on business analytics success in manufacturing companies.

H8: Data Quality mediates the effects of leadership support on business analytics success in manufacturing companies.

3. METHODS

The researchers used a quantitative, descriptive-causal research design. Thrusfield and Christley (2018) characterize descriptive research as observing a sample population in its natural setting. Descriptive research often entails gathering data through surveys, interviews, observations, or other means and then analyzing and summarizing it using statistical techniques. Because the researcher wanted to investigate the effects of data quality, user skills, and leadership support on business analytics success, the descriptive design was used to characterize the phenomenon for the observed demographics. After this, the causal design helped the researchers determine and explain how much the independent variables influence the dependent variable. A causal research approach aims to identify cause-and-effect relationships between variables. It entails modifying one variable (the independent variable) to see how it affects another variable (the dependent variable), while accounting for any other possible impacts on the connection. This

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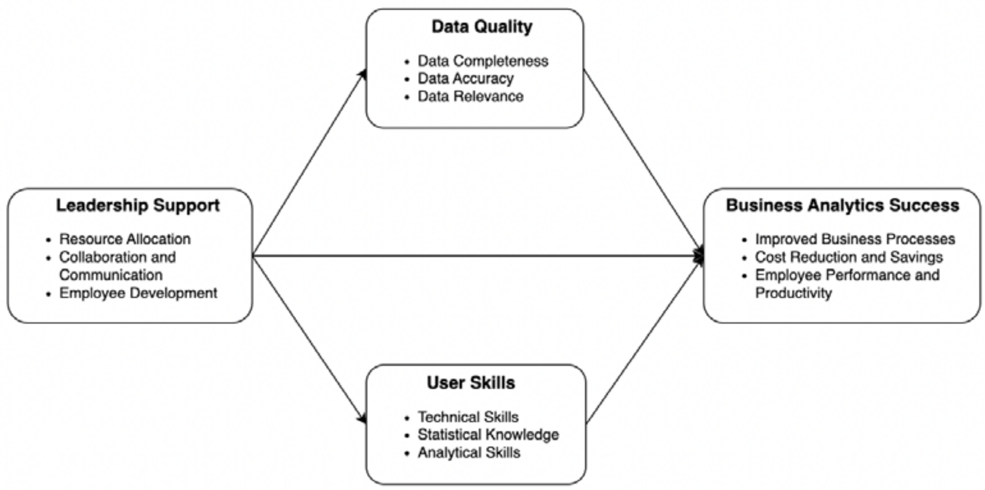
technique may quantify and assess the influence of data quality, user skills, and leadership support on business analytics success in manufacturing organizations.

Figure 1. Hypothesized Framework



The researchers developed a questionnaire tailored explicitly for personnel working in manufacturing enterprises located in the Philippines, aligning with the objectives of this study. The items were designed based on the interview results and a systematic literature review using Scopus-indexed articles in the past ten years. The questionnaire was validated by a panel of five specialists, after which it was distributed for pilot testing. Confirmatory factor analysis (CFA) was an essential procedure to establish the instrument's validity in the study. The relationships between the observed variables and their corresponding latent constructs were assessed using CFA to validate or enhance the proposed measurement model. Only items with loadings of 0.5 and above were retained. Meanwhile, the reliability assessment was conducted using Cronbach's alpha, following the standards established by George and Mallery (2018). According to their criteria, a minimum alpha coefficient of 0.7 suggests acceptable reliability and a value below 0.7 would be considered questionable, poor, or unacceptable. All scales received an alpha value higher than 0.8.

An official letter and consent form were included on the initial page of the questionnaire. In this section, participants were provided information regarding the survey's characteristics, the anticipated completion time, data administration and utilization procedures, and their freedom to decline participation. In addition, they were requested to indicate whether they were willing to participate in the study. The respondents' demographic information is asked for in the second section of the questionnaire. The Likert-type scale, comprised of the third section of the questionnaire, assesses the success of business analytics, user skills, leadership support, and data quality. Data quality assessment encompassed three key dimensions: data completeness, accuracy, and relevance. Additionally, user skills were divided into technical skills, statistical knowledge, and analytical ability. In contrast, leadership support was assessed concerning the allocation of resources, collaboration and communication, and the professional development of employees. In the end, the success of business analytics was evaluated

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based on savings and cost reductions, improvements to business processes, and employee performance and productivity. The participants' answers were classified into distinct degrees of agreement using the following coding schemes: "4" denoted strong agreement (SA), "3" agreement (A), "2" disagreement (D), and "1" strong disagreement (SD).

Data was obtained from 401 respondents coming from five manufacturing companies. They were chosen by simple random sampling done through Excel. Based on the statistics, many of the group consists of males, comprising 65.59% of the total, while females comprise 32.42%. In this category of gender, 1.5% reportedly identify as non-binary or having alternative genders, while there were two or 0.5% who preferred not to disclose their genders. Conversely, the age distribution of the group exhibits a considerable degree of diversity. The age group of 35-44 comprises 25.44% of the respondents, while the age group of 45-54 years accounts for 21.95%. 13.5% and 10.5% of the group are comprised of the age groups 18-24 and 25-34, respectively. The data further indicates that the group included those aged 65 and above (1.5%), while the most prominent group was 25-34 with 32.42%. Regarding education, a significant proportion of participants (43%) possess a minimum of a high school certificate. Approximately 23.25% of individuals have a bachelor's degree, and 21.5% own just a high school diploma. Notably, a small number of participants had a master's or a higher degree, suggesting a scarcity of individuals with advanced degrees in the community of workers in the manufacturing sector. The occupation breakdown reveals that a significant majority of the group (60.25%) is employed in production/labor, followed by administrative staff (21.5%) and technical personnel (9%). Management, research, and development professionals make up just 2% and 7.25% of the responses, respectively. The breakdown of roles in decision-making within the organization reveals that a significant portion (41.65%) of participants identify themselves as decision-makers, followed closely by contributors (32.67%). Observers make up 18.20% of the responses, while a smaller proportion (7.48%) indicated they do not have a role in decision-making processes. Understanding the distribution of decision-making roles among employees is crucial for fostering effective communication, collaboration, and organizational alignment. It provides insights into the dynamics of respondents who looked at how business analytics had been used in the workplace.

Sample items for each construct are provided in the table below:

Table 1: Sample Items from the Likert-Type Scales Used

Construct	Sample Descriptors
Data Quality	The figures reported in our company analytics reflect the true values of our manufacturing activities. Our manufacturing data captures all essential aspects of our operations. Our manufacturing data keeps up with the changes and trends in the industry.
User Skills	I am confident in my ability to operate the business analytics software tools used in our manufacturing operations. I have a solid understanding of probability and statistics and its relevance to data interpretation in our manufacturing operations. I can critically evaluate and discern the quality and relevance of the data I work with.

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Leadership Support	The company leadership provides enough personnel dedicated to the business analytics functions in our manufacturing operations.
	The company leadership has established clear channels for sharing business analytics insights across our manufacturing operations.
	The company leadership invites consultants or trainers to upgrade the analytical capabilities of the workforce.
Business Analytics Success	Our manufacturing cycle times have reduced due to optimizations driven by business analytics.
	Our inventory carrying costs have reduced due to better demand forecasting enabled by business analytics.
	Our team's performance metrics (e.g., throughput, yield, uptime) have improved since leveraging business analytics.

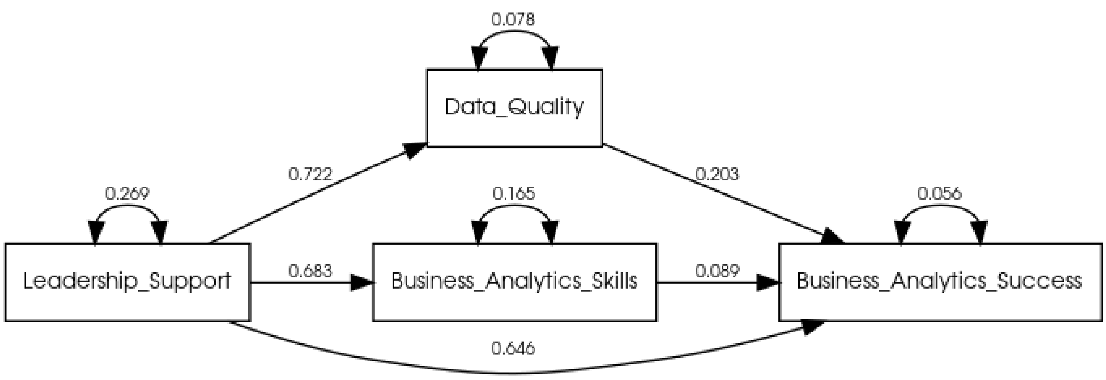
4. RESULTS

The analysis initially factored in the respondents' demographic characteristics. Subsequently, t-tests and ANOVA were conducted for each variable, with demographics as the grouping factors. At a significance level of .05, the results indicated no substantial difference in the mean ratings across various groups, except for user skills when respondents were categorized by age and years of experience. Younger employees in manufacturing companies exhibit greater confidence in their ability to comprehend analytics processes and utilize statistical tools for implementing business analytics.

A path analysis model was implemented to ascertain the accuracy of the regression model's data description. The standard errors for the estimated parameters were calculated by utilizing maximum likelihood estimation.

First, the reliability of the analysis was tested based on the sample size used to construct the model. Next, the results were evaluated using the Chi-square goodness of fit test and indices. Lastly, each endogenous variable's squared multiple correlations (R2) were examined. The results of the path analysis model are presented in Table 2, while the node diagram is shown in Figure 2.

Figure 2. Node Diagram of the Path Analysis Performed



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Sample size. A high sample size is required for factor analysis to produce repeatable and reliable factors. Kline (2023) suggests that the N:q ratio be about 20 to 1. The participant-to-item ratio for this study was about 44 to one, with a sample size of 401 and nine variables included. According to the N:q ratio rule of thumb, the sample size provided is enough to yield credible findings.

Model fit. There are many approaches to determine if the route analysis model appropriately reflects the data. Fit indices assist researchers in determining if the factor analysis model accurately fits the data. This investigation employed the comparative fit index (CFI) and standardized root mean square residual (SRMR). The CFI was more than .95, at 0.9501, indicating that the model matched the data well (Hooper *et al*., 2008). The SRMR ranged between.05 and.08, with SRMR = 0.06, indicating that the model satisfactorily fits the data (Hooper *et al*., 2008).

The regressions were tested at a significance threshold of 0.05. Leadership support strongly predicts data quality (B = 0.72, z = 26.83, p <.001), with a one-unit increase in the former leading to an extra 0.72 units in the latter. Leadership Support substantially predicts BA Skills (B = 0.68, z = 17.46, p <.001). A one-unit increase in leadership support leads to an extra 0.68 units in the expected value of BA Skills. BA Skills strongly predicted BA Success (B = 0.09, z = 3.04, p =.002), implying that a one-unit increase in BA Skills resulted in a 0.09-unit rise in the expected value of BA Success. Data quality strongly predicts BA performance (B = 0.20, z = 4.78, p <.001). Increasing data quality by one unit leads to an extra 0.20 units in anticipated value. Leadership support significantly predicts BA Success (B = 0.65, z = 15.02, p <.001). A one-unit increase in the mean rating for leadership support leads to a 0.65-unit increase in expected value for BA success.

Table 2: Unstandardized and Standardized Loadings and Significance Levels for Each Parameter in the path analysis model (N=401)

Parameter Estimate	Unstandardized	Standardized	*p*
Regressions			
Leadership Support → Data Quality	0.72(0.03)	0.80	< .001
Leadership Support → Business Analytics Skills	0.68(0.04)	0.66	< .001
Business Analytics Skills → Business Analytics Success	0.09(0.03)	0.09	.002
Data Quality → Business Analytics Success	0.20(0.04)	0.19	< .001
Leadership Support → Business Analytics Success	0.65(0.04)	0.66	< .001
Indirect Effect of Business Analytics Success on Leadership Support by Business Analytics Skills	0.06(0.02)	0.06	.003
Indirect Effect of Business Analytics Success on Leadership Support by Data Quality	0.15(0.03)	0.15	< .001
Total Effect of Business Analytics Success on Leadership Support	0.85(0.02)	0.87	< .001
Errors			
Error in Data Quality	0.08(0.006)	0.36	< .001
Error in Business Analytics Skills	0.16(0.01)	0.57	< .001
Error in Leadership Support	0.27(0.02)	1.00	< .001
Error in Business Analytics Success	0.06(0.004)	0.22	< .001

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Note. $\chi^2(1) = 62.21$, $p < .001$; -- indicates the test was not conducted as the observed variance/covariance values were used.

Thus, the data and resulting analyses supported all the hypotheses proposed. Furthermore, the variances explained by the model are of practical significance, as revealed in the squared multiple correlations.

Squared multiple correlations. The model's regressions were assessed by examining the R2 value of each endogenous variable. The R2 value provides insight into the extent to which the model's regressions explain the variability in the endogenous variable. If an endogenous variable has an R2 value of ≤0.20, it indicates that the regression(s) in the model do not adequately explain that variable, and in such cases, it is recommended to exclude all regressions related to that endogenous variable from the model (Hooper *et al*., 2008). Notably, none of the endogenous variables exhibited R2 values of ≤0.20.

Table 3: Estimated Error Variances and R^2 Values for Endogenous Variables in the SEM model.

Endogenous Variable	Standard Error	R^2
Data Quality	0.08	.64
Business Analytics Skills	0.16	.43
Business Analytics Success	0.06	.78

In the context of a manufacturing organization, the effectiveness of business analytics is significantly impacted by several critical elements, the most prominent of which is the support provided by leadership. The successful implementation of business analytics, distinguished by its capacity to optimize employee performance and productivity, decrease expenses, generate savings, and streamline operations, is contingent upon solid backing from executives within the organization.

The most influential factor contributing to the success of business analytics is leadership support, which includes ass*et al*location, communication and collaboration, and employee development. The support provided by organizational leaders significantly influences the endorsement of initiatives and progress based on data.

Resource allocation is a component of leadership support that ensures the required financial and human resources are allocated to business analytics initiatives. By doing so, the organization can fund the implementation of sophisticated analytics tools, enhance employee training initiatives, and establish a resilient data infrastructure — all critical for achieving favorable analytics results. In addition, the promotion of knowledge sharing, cross-functional cooperation, and the synchronization of analytics endeavors with organizational objectives are all outcomes of effective communication and collaboration facilitated by leadership. Effective communication channels enable intelligent decision-making at every level of the organization by promoting the dissemination of insights derived from analytics across departments. Additionally, leadership backing for employee development emphasizes the significance of ongoing education and the improvement of skills in data analytics. Leaders enable employees to optimize their prospective contributions to analytics initiatives by furnishing them with training opportunities, mentorship, and a nurturing learning environment that fosters the development of their technical faculties, statistical expertise, and analytical prowess.

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However, it is critical to note that user skills and data quality partially mediate the relationship between leadership support and business analytics success. As a mediator, data quality ensures that the insights derived from analytics are founded upon quality data characterized by completeness, relevance, and accuracy. In the same way, user skills, which include technical proficiency, statistical expertise, and analytical acumen, influence the impact of leadership support by empowering personnel to utilize analytics tools efficiently and interpret data to extract practical insights.

A fundamentally interconnected model in the era of data-driven decision-making demonstrates how leadership support is the principal determinant of success in business analytics, with user skills and data quality acting as mediating factors. Manufacturing companies can achieve long-term growth and competitive advantage in the twenty-first century's data-centric business environment by prioritizing leadership support, allocating resources toward improving data quality, and encouraging the development of user skills.

5. CONCLUSION

Within the domain of business analytics, the support of leadership becomes a critical determinant of achievement for manufacturing organizations. The statistical analyses, which were performed at a significance level of 0.05, highlighted the substantial impact that leadership support has on critical outcomes. It is worth noting that leadership support was a strong predictor of both business analytics skills and data quality, with a substantial increase in value expected with each one-unit increment. Furthermore, the analyses unveiled that the achievement of business analytics was significantly influenced by the backing of leadership, underscoring the critical nature of such support in cultivating triumphs in analytics initiatives within an organization.

Although leadership support is critical for successfully implementing business analytics, user proficiency and data quality mediate its effects. A partial mediation model was validated, indicating that although leadership support directly impacts the effectiveness of business analytics, its effects are also mediated by these intermediary variables. User skills, including technical expertise and analytic prowess, enable staff members to utilize analytics tools effectively. On the other hand, data quality guarantees the precision and applicability of insights obtained from analytics initiatives.

In summary, the results emphasize the interdependence between user proficiency, data integrity, leadership endorsement, and the achievement of business analytics objectives in manufacturing establishments. Organizations can foster a favorable environment for harnessing analytics to achieve informed decision-making, operational efficiency, and long-term competitive advantage in the data-centric twenty-first century by placing leadership support as a top priority and allocating resources toward improving user skills and data quality.

Recognizing the universal significance of leadership across diverse organizational contexts and the potential for business analytics to transcend industry boundaries, coupled with the robustness of the proposed model, the paper's impact may reach far beyond the confines of the manufacturing sector in the Philippines. Delving deeper into these insights could unveil the broader applicability of these findings across varied markets, showcasing how these fundamental principles can be effectively implemented beyond the manufacturing industry.

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