Shahjalal University of Science and Technology, Sylhet – 3114.

Department of Business Administration.

"The Way Business Analytics (BA) Lead to Successful Decision-Making Effectiveness (SDME): A PLS-SEM (Partial Least Square Structural Equation Model) Analysis."

Course Title: Internship Report

Course Code: BUS - 411

Submitted To

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Date of Submission: 13th December 2023

Letter of Submittal

8th December 2023

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Subject: Submission of Thesis Report.

Honorable Sir,

With due respect, I would like to inform you that it is a great pleasure for me to submit the thesis on **"The Way Business Analytics (BA) Lead to Successful Decision-Making Effectiveness (SDME): A PLS-SEM (Partial Least Square Structural Equation Model) Analysis."** you assigned me as a requirement for the completion of the BBA program. I have devoted the last few months to gathering information, evaluating it, and combining my results into a thorough document that fulfills the goals stated in the thesis proposal. I'm happy to let you know that the thesis is currently complete.

I am making sure that the thesis complies with the strictest academic requirements and is formatted by the specifications provided by the Department of Business Administration, SUST.

Therefore, I hope you will accept my thesis paper and permit me to deliver it to the examination committee.

Sincerely Yours,

Mahraj Hussain Shohag

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Declaration of Originality

8th December 2023

I do certify that the thesis paper "The Way Business Analytics (BA) Lead to Successful Decision-Making Effectiveness (SDME): A PLS-SEM (Partial Least Square Structural Equation Model) Analysis" is my original work completed for my Bachelor of Business Administration degree for fourth year second semester. The text and other materials in the report do not include any copyright breaches or offenses on the intellectual property of third parties.

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Acknowledgment

In the name of Allah, the Most Gracious, the Most Merciful. All praise is due to Allah, the Lord of all worlds, the Most Compassionate, the Most Merciful. It is with immense gratitude and humility that I acknowledge the guidance, strength, and wisdom bestowed upon me throughout the journey of completing this thesis. All thanks and praise are due to Allah alone.

I extend my heartfelt appreciation to my supervisor, Dr. Md Khairul Islam, for his unwavering support, expertise, and mentorship.

Also, my family, whose encouragement and support have been a source of strength, I extend my deepest gratitude. Their belief in me and unwavering encouragement have been my pillars of strength.

Moreover, I am deeply indebted to the respondents who graciously participated in this study. Their willingness to share their experiences and perspectives has been pivotal in developing this research, and I am sincerely thankful for their contribution.

Dedication

This is Mahraj Hussain Shohag, author of the thesis paper **“The Way Business Analytics (BA) Lead to Successful Decision-Making Effectiveness (SDME): A PLS-SEM (Partial Least Square Structural Equation Model) Analysis.”** Dedicating my thesis to my beloved

“Nana” (Grandmother) – The Late Mrs. Begum Noor.

She was the one who dedicated herself to the preliminary stage of my educational life. Ignoring the unbearable summer heat, torrential rains, and foggy winter mornings, she took me to school every morning for seven consecutive years and did not care about anything. Not even the loads of her age. But, before I could do anything for her, she died on 28th December 2015. No matter what I do, nothing will be contemporary to hers. May Almighty Allah forgive her and grant her the Jannatul Ferdaus. Amen.

Table of Contents

"The Way Business Analytics (BA) Lead to Successful Decision-Making Effectiveness (SDME) : A PLS-SEM (Partial Least Square Structural Equation Model) Analysis"

1. Abstract: The domain of business analytics has gained significant significance in the contemporary corporate landscape for enhancing the efficiency of decision-making. This study emphasizes the transformative power of data-driven insights when it comes to the intricate connection between successful decision-making and business analytics. Although the increasing use of business analytics for insights driven by data in terms of making decisions, there is less study on how it may be used to upgrade the effectiveness of making decisions at the bottom level of the organization. This study establishes a research framework that links corporate analytics to the effectiveness of organizational decision-making by utilizing the view of information processing and contingency theory. Structural equation modeling is employed to assess the study model using 220 collected responses from commercial entities in Bangladesh. The major findings indicate that Business Analytics has a favorable effect on Information Processing Capability through the mediation of a Data-Driven Environment. This, in turn, leads to improved Decision-Making Effectiveness. Information Processing Capability has a beneficial impact on both Data-Driven Decision-Making and Decision-Making Effectiveness. Based on the inquiry, it has been observed that the effectiveness of successful decision-making is greatly influenced by both data-driven decision-making and the making of effective decisions. However, the impact of making effective decisions may be disregarded. Ultimately, it can be concluded that with the exception of Decision-Making Effectiveness, all the factors influenced the path to Successful Decision-Making Effectiveness in a meaningful and anticipated manner. Data-Driven Decision-Making had the greatest significant influence on the effectiveness of successful decision-making among those constructs.

2. Introduction: Business analytics is the discipline that involves gathering diverse insights from several sources and using that knowledge to create informed and successful decisions to drive corporate growth. Business analytics refers to the comprehensive utilization of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to inform and guide decision-making and subsequent actions [1]. Data usage refers to the process of making effective judgments by analyzing and interpreting statistics and data-driven analysis. Business analytics encompasses the abilities, technology, and methodologies used to systematically and repeatedly examine and investigate previous business performance to obtain an understanding and guide corporate planning [2]. The concept of business analytics originated in the mid-1950s and has been a matter of considerable research ever since. Gradually, as the company has progressed, the significance of making efficient decisions in the business realm has grown. The importance of Business Analytics has been attributed to various factors. Firstly, advancements in information technology have facilitated firms in devising novel methods to gather data from both internal and external sources [3]. As time passes, the field of information technology (IT) is rapidly expanding worldwide across several industries. Business analytics is included in that list as well. At the same time, big data presents significant commercial prospects for firms to acquire valuable insights into consumers and operations [4]. In this way, organizations are increasingly utilizing Business Analytics. Secondly, business companies necessitate the utilization of Business Analytics to get a competitive advantage by making more informed and expedient selections [5] companies are seeing heightened competitiveness and instability in their markets as a result of rapid technical progress and globalization [6]. Thirdly, to enhance operating efficiency. In addition to generating financial profits, analytics can be utilized to optimize and refine business procedures and activities. Finally, the convergence of large data, IT advancements, and analytics used in business has elevated making decisions to an unprecedented degree that is heavily reliant on data, enabling managers to see what was previously imperceptible [7]. Undoubtedly, every management aspires to outperform their peers in the realm of business. Given the existence of a tool such as Business Analytics, individuals and organizations will seize the opportunity to enhance their growth by utilizing it. Business Analytics holds immense importance in the contemporary business landscape, therefore making it a subject of extensive research. Regrettably, there have been limited academic inquiries specifically aimed at comprehending Business Analytics and its associated sectors. Consequently, there is limited understanding of the impact of analytics in business on enhancing the matter of making decisions and achieving success. Several organizations are attempting to get a handle in terms of applying analytics in business functions [5, pp. 47-52], [7], [8], The absence of comprehension poses an obstacle for firms to efficiently utilize Business Analytics to generate value. Once the effect of analytics in business on making decisions is comprehended, the potential value of business analytics can be clearly described.

This research seeks to tackle the lack of understandability by examining the methods by which Business Analytics improves Successful Decision-Making Effectiveness (SDME), which refers to the extent to which a decision achieves the intended outcomes. Furthermore, this study will extend beyond the realm of efficiently making decisions. Moreover, it will examine the matter efficacy of the process of making decisions. This study provides an empirical evaluation of a method that describes the interaction between business analytics and other organizational terms to enrich the effectiveness of decision-making. Prior research has employed the view of processing information to recognize the influence that information technology has on firms. one research [6] A study has been undertaken on Business Analytics and its effect on making decisions effectively. Furthermore, the aforementioned study was carried out on company enterprises located in the United Kingdom. Nevertheless, there has been no actual research undertaken to ascertain the practical success of applying business analytics in decision-making within the business domain. This research aims to enhance the existing literature by constructing a conceptual framework for conducting research that examines the influence on Decision-Making Effectiveness of Business Analytics. The primary objective is to assess the success of decision-making based on the developed model and relevant constructs. To empirically assess this research model, the method employed is PLS-SEM in SmartPLS 4 software. This analysis is performed using insights obtained from an online questionnaire survey of 220 business organizations in Bangladesh. As previously stated, a prior study focused on business organizations in the UK and identified a gap in confirming the practical success of decision-making through the use of business analytics in the business sphere. Hence, this research is focused on the perspective of Bangladesh, and this article will conclude by examining the business organizations in Bangladesh.

This study demonstrates that the utilization of Business Analytics within a Data-Driven Environment (DDE) would result in the enhancement of Information Processing capacity (IPC), which subsequently has a significant influence on corporate decision-making and Decision-Making Effectiveness (DME). Has the implementation of Business Analytics on Successful Decision-Making Effectiveness (SDME) been identified in the practical business field? This study will further strengthen managers' understanding of business analytics and its impact, hence improving effective corporate decision-making.

3. Theoretical Background:

3.1. Explanation of Key Concepts: The primary objective of an organization is to effectively handle and control uncertainty from the perspective of information processing [9], [10]. Managing uncertainty involves utilizing gathered knowledge and a systematic approach to facilitate decision-making and ensure confirmation of the chosen course of action. For example, the complexity of tasks and the speed at which the environment changes can be addressed by implementing information processing techniques [6]. The insights from processing information emphasize the significance of comparing information processing specifications with IPC: the higher the uncertainty in tasks, the higher the amount of data that must be analyzed [9]. To reduce ambiguity and enhance decision-making, it is crucial to have access to the greatest amount of information feasible. By analyzing the gathered data, one can effectively make a sound judgment and reduce ambiguity. Organizations should optimize their operations of a business to streamline the processing of information, allowing those who make decisions to effectively analyze a significant volume of information. This will enhance decision-making, save costs, and ultimately improve overall organizational performance. An organization's Information Processing Capability (IPC) refers to its ability to effectively acquire, consolidate, and evaluate data and information, and utilize the knowledge derived from them to inform decision-making within the company [6]. Identical definitions have been employed in many research areas. Information capabilities encompass the activities of collecting, analyzing, and disseminating information within the framework of strategic human resource management. [11]. Alternatively, information processing capability refers to the extent of technological assistance provided by IT systems for different tasks within the context of an inter-organizational supply chain [12]. Premkumar *et al.* [13] demonstrated that The interplay between information processing requirements and Information Processing Capabilities (IPC) has a substantial impact on performance within the framework of an inter-organizational supply chain. This suggests that when an organization recognizes the need for information processing and analysis and is capable of carrying out these tasks, it has a significant impact on the activities and performance within the context of the supply chain. Similarly, Wang *et el.* [14] described that A direct correlation exists between interfirm IPC (Information Processing Capabilities) and the success of supply chain companies. A company is considered more efficient when its needs for processing information are in line with its capabilities in this area [10].

[15] Introduces the idea of IPC (Information Processing Capability) to analyze organizational architecture from an information processing standpoint, without explicitly defining it. These terms are taken [10, p. 614], to enhance the information processing perspective, it is important to understand that the processing of information indicates to the collection, interpretation, and integration of data. Based on a thorough examination of existing literature, IPC (Information Processing Capability) can be precisely described as an organization's capacity to gather, combine, and evaluate data and information, and utilize the resulting insights to make informed decisions.

The next term to be explored is denoted as the organization's DDE. The term “data-driven” refers to the practice of using data analysis and interpretation as the basis for decision-making. Hence, a data-driven environment signifies a meticulously structured organizational framework, whereby decisions are made utilizing data calculation, analysis, and interpretation. An organization's Data-Driven Environment (DDE) refers to the set of practices and strategies implemented by an organization to guide and support its analytic efforts. This includes defining explicit strategies and policies, as well as building the organizational structure and procedures to enable and promote Business Analytics activities [6]. Setting up a Data-Driven Environment (DDE) is crucial for any company that wants to reap the benefits of Business Analytics. One way to accomplish this is by developing a customized plan, set of rules, organizational framework, and set of business procedures that support and enhance the operations of Business Analytics [16], [17], [18], [19].

The subsequent pivotal concept to be examined is DDM (Data Driven Decision Making), which refers to the utilization of data by firms to produce well-informed and efficacious decisions. Organizations embrace novel ideas in the context of DDM (Data Driven Decision Making), even if these ideas contradict the current decision-making practices. Similarly, the saying of [17], [19], [20] the level of an organization's receptiveness to novel ideas that question existing practices, grounded on data-driven understanding; possesses the necessary data for decision-making; and uses insights derived from data to make decisions and create new products and services.

The business plan, end-user comprehension, and integration into organizational processes are the three most important factors in ensuring that analytics-driven insights are used effectively and lead to new actions across the organization [18, p. 22]. In this way, suggestions from the previous studies [1], [7], and [21] state that, analytically driven strategy, relevant businesses, and organizational structure respectively are important to develop to integrate business analytics into organizational procedures, which will enhance decision-making and DME. However, while these factors are absent, a corporation will lack the knowledge of which data to prioritize, how to distribute analytical resources, and the objectives it aims to achieve in a data-to-knowledge program [16, p. 122]. Based on previous research, it is evident that incorporating Business Analytics into organizational processes is highly important. To accomplish this, an organization must develop analysis-driven tactics and strategies that align with the business and its functions.

When faced with ambiguity, making judgments based on evidence might be the determining factor between success and failure. Nevertheless, the ability to make sound decisions does not necessarily ensure a successful outcome in the face of ambiguity. Multiple variables could contribute to the situation. The decision may be efficacious, although it is not facile or expeditious in its execution. Furthermore, a decision that fails to contribute to the establishment of an organization's distinct value in the market cannot be deemed as effective. Put simply, a move can be considered truly successful when it generates substantial value for the firm in the current market. The decision-making process may not have been suitable for the specific uncertainty encountered by the business. However, the decision that was made proved to be effective in a different context or for another organization. Another crucial aspect in determining the success of a decision is clearly articulating the requirements and desired outcomes. The primary factor in the decision-making process is establishing precise specifications for the desired outcomes of the decision. What are the specific goals that the decision needs to achieve? What are the minimum objectives it must achieve? What are the criteria it must meet? Within the realm of science, these phenomena are referred to as “boundary conditions”. For a choice to be effective, it must meet the necessary boundary criteria. [22].

3.2. Objectives of the Study: The first and foremost objective of the study is, based on the established research model and existing literature, which of the constructs influences the most to make Successful Decision-Making Effectiveness (SDME).To assess the impact of Business Analytics on decision-making efficiency. Examine the influence of business analytics tools and methodology on an organization's process of making decisions. Determine the extent to which business analytics improves the accuracy, timeliness, and overall effectiveness of decision-making.

Secondly, Analyze Data Quality's Impact on Business Analytics Decision-Making. Examine how the quality of the data affects how well business analytics assist in making decisions. Provide methods for improving the integrity and quality of the data to guarantee more trustworthy and precise decision-making.

Thirdly, examine the impact of business analytics on organizational performance over a while. Analyze the enduring impacts of business analytics on the overall efficiency of the organization. Analyze the influence of continuously using and enhancing analytics on strategic decision-making and organizational achievement.

Moreover, out of six constructs, which construct made the most significant impact on Successful Decision-Making Effectiveness?

Lastly, in the competitive business world, what could be the future strategy to enhance successful decision-making will be established?

4. Hypothesis Development Based on Existing Literature, Key Terms, and Their Interrelation:

4.1. Business Analytics and Information Processing Capabilities: According to the previous researchers' study [16], [17], [20] Applying Business Analytics can enhance an organization's Information Processing Capability (IPC) by enabling effective data analysis and leveraging the resulting insights for informed decision-making, ultimately leading to improved organizational performance. In an earlier explanation, we have shown that the amount of data that needs to be processed increases in direct proportion to the degree of job insecurity [9]. In this regard, to reduce the uncertainty an organization will deal with a huge amount of data and insights. It will lead the organization to rely on Business Analytics. Eventually, relying on Business Analytics will lead to increased Information Processing Capability (IPC). So, depending on that analysis we can establish that,

H1: Business analytics directly and favorably impacts Information Processing Capability.

Dealing with more information helps reduce uncertainty and analyzes the greater amount of insights required for Business Analytics to generate benefits from the business. In this regard, Business Analytics needs support. And the support might come from a well-structured environment. The better the data-driven environment is, the better the benefits from Business Analytics could be generated. Many studies that have taken place before support the idea. Research on Business Analytics has shown that for companies to reap the benefits of this tool, they must create a Data-Driven Environment (DDE) to accommodate their Business Analytics software [4], [16], [17], [20], [19]. It shows that the importance of the fit between a Data-Driven Environment and a Business Analytics (BA) can be better understood with the help of contingency theory.

Fit is described by contingency theory as, how well the needs, wants, goals, aims, and structures of one part match up with those of another part [23, p. 45], and speculates the performance is due to that orientation [24]. According to some previous studies [25], [26], the contingency theory has been widely utilized to investigate the connections among many elements such as IT, organizational issues, and organizational performance [6]. And, by saying of [27], [28] these IT business value studies demonstrate that the collaboration between organizational and IT components can result in the development of diverse IT capabilities. This, in turn, allows a firm to utilize technology as a means of distinguishing itself from competitors. [29]. When Business Analytics and a Data-Driven Environment work together in a company, it improves its IPC. This assertion is substantiated by studies on the business benefits of information technology and previous research on business analytics. A company that has a greater alignment between its BA and DDE has potential to achieve better performance compared to an organization with a lower alignment. Additionally, the level of fit is enhanced by a stronger Information Processing Capability (IPC). The impact of this fit-on Information Processing Capability (IPC) can be understood by considering the argument that technology plays a crucial role in shaping the processing, and structure of an organization, as suggested by the theory of contingency. This argument can be used to support a mediation model of fit [29]. [30] Claimed that for optimal performance, growing technological complexity will necessitate increased structural complexity. On the other hand, [31] stated that organizational structure and procedures may be influenced by technology. Alternatively, [32] analyzed the relative routineness of employment and argued that technology is a necessity for organizational structure. Explicitly defining organizational direction, policy, framework, and operational procedures to facilitate Business Analytics operations can assist in upgrading the processing capabilities of information. Consequently, the company is likely to get immersed in a Data-Driven Environment. So, depending on that theoretical analysis we can establish that,

H2: Through the arbitration of a Data-Driven Environment, Business Analytics has an advantageous and indirect impact on Information Processing Capabilities.

4.2. Organizational Environment Driven by Data, Processing Capability of Information, and Making Decision: When an organization develops its structure, it is more likely to make effective judgments, according to the information processing view [10]. Besides that, those organization develops proper business processes [13], and Simplify and clarify decision rights across the organization [33] to increase its capacity for information processing in order to meet its data processing needs. For example, the processing demand of large data is intricate due to the need to handle data that are abundant in volume, diversity, and velocity [6]. Organizations find this data processing requirement daunting since individuals frequently find it difficult to adequately digest incoming information in huge volumes [34, p. 156] for an organization to effectively utilize Business Analytics to generate value in business. It is necessary to establish a Data-Driven Environment (DDE) by formulating a precise framework, policies, procedures, and organizational strategy that support and enable the operations of Business Analytics [16], [16] - [19]. Traditional systems cannot collect, store, and evaluate massive data [16], [35]. To address its large information processing requirements, a business must upgrade its capability to process information by implementing usable Business Analytics tools. This can be achieved by adopting an "analytically driven strategy" [1], developing essential business procedures [7], and organizational structure [21].

The higher the capability to deal with data, the better the decision-maker the organization could be. At the same time, the organization should have sufficient data and information to deal with. Eventually, it helps a firm to improve its business practices and better decisions. One of the researchers supported the theoretical logic stated earlier. According to [35], An organization should possess a sufficient amount of data and data-driven insights to assess its business operations and make well-informed decisions. Both internal company efficiencies and the creation of new consumer goods and services can benefit from this. In this scenario, a business has successfully built a robust Information Processing Capability that aligns with its data processing needs, resulting in improved efficiency and adaptability [36], and greatly enhancing its performance [15]. It is not sufficient to collect information and analyze it. Rather, developing the processing capability of gathered information. In addition, processing that information as fast as possible so that making decisions might be easier. For instance, When a company has complete and precise knowledge about the connection between decisions and results, It will have the highest likelihood of making wise choices [37], coming up with effective organizational strategies [38], and enhancing organizational effectiveness [39]. Therefore, by analyzing all theories we can establish that,

H3: IPC positively influences DDM.

H4: IPC has a direct as well as favorable impact on DME.

A tree can produce a huge amount of oxygen in its lifetime. In this way, if we can create a garden consisting of those trees, a visual margin of produced oxygen can be seen. Similarly, let's compare the trees with Business Analytics (BA), and the garden with a Data-Driven Environment (DDE). Establishing a Data-Driven Environment allows Business Analytics to reach its full potential by basing strategy, operations, and decision-making on insights obtained from data [1], [17], [20]. A Data-Driven Environment is believed to facilitate an organization in acquiring the requisite data for decision-making, being open to innovative concepts, making informed judgments, and leveraging factual insights to create novel services or products. So, the following can be proposed,

H5: DDE certainly manipulates DDM.

H6: DDM is favorably amalgamated with DME.

It is clear to predict that the bigger the organization size, the higher the effects of it on other organizational aspects e.g., IT (Information Technology). Evidence found that the size of a corporation is significant since it can influence the correlation between IT and other organizational factors, including the utilization and expenditure patterns of IT investments. [40], [41]. Furthermore, the data reveals a direct correlation between size indices and firm profitability [42]. According to [26], and [43], the interconnection between Information Technology and firm size is a significant aspect of research.

It is also highly possible that the size of a company could potentially influence the quality of the final output of its system [44]. Additionally, it has been observed that large corporations possess greater competitive prowess in industries that need competition, as compared to small businesses [42]. Regarding knowledge management, the results about the moderating effect of company size differ across different domains, as stated by [45], and [46]. However, the influence of business size should not be disregarded. The research identifies whether Business Analytics (BA) influences Decision-Making Effectiveness (DME), and eventually, leads to success (Successful Decision-Making Effectiveness, SDME) or not. Previous research like [40], [41], indicates that businesses of varying sizes behave differently when it comes to IT use and investment. However, other studies have found, where it is established that firm size does not impact the research model related to Business Analytics. For example, [6] proposed their study by rejecting the hypothesis "Firm size moderates the proposed path" on Business Analytics suggesting that the size of an organization does not impact the path in their analysis. So, in our research, we do not include that investigation. Industry type is another crucial factor because businesses in various industries frequently exhibit systematic differences in IT spending, IT requirements, and other organizational and technological aspects that affect how IT is used [47]. While IT research hasn't given much thought to how different industries affect IT [47], However, additional research conducted in other academic disciplines has revealed evidence supporting the notion that an organization's efficacy is moderated by its industry. For example, [48], [49]. Similar to this, it is anticipated that industry type will probably have a moderating effect on Business Analytics applications. However, After investing in some existing literature, in most of the cases it is found that industry type weakly moderates the research model that is related to Business Analytics. For instance, the statement "Industry type moderates the proposed path" is weakly supported by [6]. As a result, we are also rejecting analyzing it.

Successful Decision-Making Effectiveness (SDME) is the last major construct to examine. Decisions made with more precision and efficiency are one of the main benefits of data-driven decision-making. Data allows companies to learn a lot about their customers, the market, and how well their operations are running. Possible opportunities and well-informed judgments can be found using these insights [50]. So, we can say that.

H7: DDM positively influences SDME.

Effective decisions based on data might mean the difference between winning and losing while dealing with uncertainty. Effective decision-making, however, does not ensure success as a result of that ambiguity. Many elements could be at play in this situation. Although not simple or particularly quick to make, the decision may turn out to be effective. Additionally, a choice cannot be deemed effective if it does not contribute to the development of an organization's distinctive value in the marketplace. To put it another way, a choice is said to be successfully made when it significantly benefits the firm in the current market. The organization may not have been able to make the best choice given the uncertainty it was facing, but the choice was nonetheless sound in terms of a different circumstance or for a different business. Declaring the goals and specifications is a crucial step in determining whether a choice is successful. So, we can propose,

H8: DME might favorably manipulate SDME.

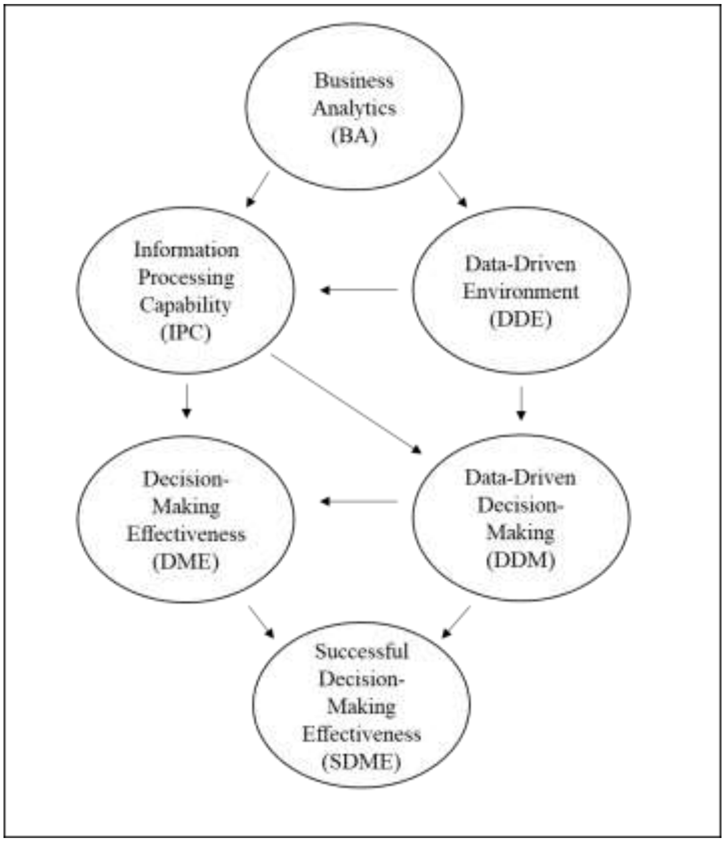

Figure.1 – Research Framework

5. Research Methodology: Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed to evaluate the hypotheses derived from survey data. Partial Least Squares (PLS) is a statistical technique used in Structural Equation Modeling (SEM) that allows researchers to simultaneously assess many relationships. It is advised that PLS-SEM be used in research scenarios where the theory is less developed [51], [52], [53], in research scenarios where the phenomenon being studied is novel, the goal is to predict or explain correlations among a set of constructs [54], [55], [56]. Even though Business Analytics' significance has been widely debated, it is still a relatively new field of study. As a result, there is not much empirical research that explores the connections between Business Analytics and other organizational variables, and there aren't many created measures for novel constructs in this field. PLS-SEM is considered suitable for the current study's conceptualization and also empirical examination of connections between Business Analytics (BA) and Successful Decision-Making Effectiveness (SDME). Since PLS-SEM can effectively handle both formative and reflective components, which are both utilized in the study model, it is also deemed suitable for this paper. The subsequent section outlines the procedures involved in the development, validation, and distribution of instruments.

6. Data Collection: For the purpose of data analysis and testing the established hypothesis, three distinct industry sectors have been chosen. In Bangladesh, industries can be categorized into three sizes: small (employing no more than 50 individuals), medium (employing 50 to 250 individuals), and large (employing more than 250 individuals). It is anticipated that businesses of different sizes may employ varying types of business analytics tools, policies, and strategies. After that, Each construct in the questionnaire survey is measured utilizing a Likert scale with five points. Initially, the questionnaire was distributed to adjacent participants to ensure their comprehension of the questionnaire's inquiries. At the early stage, the questionnaire was in MS Excel form, and It was necessary for the participants to complete the survey and return it to the author. Logically, the process was time-consuming and demotivating for the respondents to respond. After understanding the consequences, a Google Form has been created to gather the data from the respondents. All of a sudden that step boosted the response rate. In terms of finding the appropriate respondents, two major categories have been considered. The previously known professional respondents, for example, internship officers, university seniors those who studied together and met previously in the university. And previously unknown professional respondents. Those who are previously known were connected to the author online e.g., Facebook, Messenger, WhatsApp, and so on. So, it was straightforward to reach out and get a response from them. The previously unknown respondents were connected to the author via LinkedIn, Facebook, and so on. A formal message has been sent to the previously unknown respondents with the Google Form link so that they can easily respond to the questionnaire. The invitation message has been sent to 343 people consisting of known and unknown respondents. Out of these 343 invitations, most of them helped and were interested in filling out the questionnaire. Around 220 respondents filled out the questionnaire, which was 64.14% in proportion. An excellent response rate in a survey is defined as 50% or higher [57]. The proportion signifies a notable level of response rate. Responses were automatically inputted into a Google sheet via Google form, as the respondents responded in it. After that the data was collected from the Google sheet to MS Excel, then SPSS, and Smart-PLS to analyze.

7. Research Model Constructs: The research model is developed and tested using several recognized and compiled constructs that are added below. There aren't many previously validated measuring items for Business Analytics because it is still a relatively new field of study. Consequently, six (6) novel formative constructs in this study have been developed based on the existing literature on Business Analytics and the value it brings to IT businesses.

Establishing formative conceptions accurately might be challenging [56] Due of limitations, the methods for developing scales that have been proposed in previous studies have limitations [58]. The reliability of ideas and statistical findings can be severely compromised by poorly defined concepts [58], might potentially impact the process of theory building and theory testing. In order to prevent typical errors in specification, we have devised six constructs that are derived from the four choice criteria [59], [6] : 1. The causal relationship between a construct and its indicators, 2. the capacity to use different indicators interchangeably, 3. the correlation among different indicators, and 4. the network of relationships that support the validity of the indicators.

Business Analytics (BA) is employed as an illustrative instance to enhance the clarity and dependability of the development process. Considering previous research [60], [16], [20], 13 different factors are used to define Business Analytics (BA) formatively at two stages: Prior to and subsequent to the gathering of data [59]. Prior to data collection, determining The main selection criterion is Business Analytics' causation to its indications. Business Analytics can be better understood as a complex concept that is formed by its indicators, each of which represents a distinct characteristic of the overall concept, rather than considering the indicators as the defining elements of Business Analytics. For example, simulation and model management are two different fields that mostly deal with models, while web analytics is all about analyzing digital data. Thus, modifications to each indicator would have resulted in modifications to the definition and interpretation of Business Analytics. Second, are the indicators interchangeable? [6]. For example, whereas optimization and model management both focus on modeling, web analytics, and social media analytics have a common theme that centers on the study of digital data. As a result, the indications cannot be used interchangeably, and the properties of Business Analytics may alter if the indicators are removed. Third, is it anticipated that the indicators would vary from one another? This question does not have a straightforward yes-or-no response. It is reasonable to assume that indicators with similar themes, for example, ones that look at digital data are more likely to be different from ones that are about different things. As a result, it appears that Business Analytics is multidimensional rather than unidimensional, which might be confirmed by performing a factor analysis following data collection. Eventually, it is not required to provide an answer to the question of whether the indicators share the same antecedents and outcomes. For instance, whereas modeling can be implemented by any company processes, employing web analytics to examine digital data may be motivated by e-commerce endeavors. As a result, their effects may vary. This argument advocates for classifying Business Analytics as a multidimensional concept. Indicators that center on digital data analysis should be categorized and characterized as a reflective construct due to their shared theme and interchangeable nature. This principle should also be applied to modelling indicators [6]. Therefore, it is considered more suitable to define Business Analytics (BA) as a higher-level component that consists of several lower-level components before collecting data. Following the acquisition of data, the lower-order components that are reflected are determined through the utilization of an Exploratory Factor Analysis (EFA).

8. Sample Size and Data Screening: A Priori Sample Size Estimation determines the necessary sample size for a study employing a structural equation model (SEM), based on the number of observable and latent variables in the model, the expected effect size, and the acceptable levels of probability and statistical power. The calculation provides two results: the minimum sample size needed to detect the specified effect, and the minimum sample size needed considering the structural complexity of the model.

In his Technical Report titled “THE IMPORTANCE OF A PRIORI SAMPLE SIZE ESTIMATION IN STRENGTH AND CONDITIONING RESEARCH”, Travis W. Beck from the University of Oklahoma's Department of Health and Exercise Science in Norman, Oklahoma, argued that Priori Sample Size Estimation should be utilized [61]. Moreover, the existing literature of numerous researchers also motivates to use it.

Sample size estimation during study design necessitates three distinct steps: (a) Choose the desired level of significance, (b) Determine the power level that has to be attained, and (c) Estimate the effect size for the experiment.

Conducting a priori power analysis for sample size estimation entails predicting the effect size that the researcher anticipates observing in the experiment. The significance threshold and power are often predetermined, often set at specific values such as 0.05 and 0.80, respectively. Therefore, the sole determinant of sample size is the magnitude of the effect, where larger effect sizes necessitate fewer sample numbers (with a fixed power and significance level), and vice versa. Therefore, choosing a suitable effect size is crucial as it directly impacts the required sample size when the power and significance levels are set.

Statistical power refers to the ability of an experiment to detect a treatment effect if it actually exists. In other words, statistical power refers to the researcher's capacity to reject the null hypothesis when it is actually incorrect. Statistical power is commonly conceptualized by researchers as the rate of Type II errors (β). β is the likelihood of incorrectly accepting a null hypothesis that should have been rejected. Power, on the other hand, is equal to 1 - β. For instance, in an experiment where the β value is 0.20, the statistical power is 0.80, indicating an 80% probability of correctly identifying a genuine treatment effect. Power is influenced by three factors: (a) the significance level (α), (b) the effect size or magnitude of the treatment effect, and (c) the sample size (n) [62]. Out of these three criteria, the researcher has the ability to alter only the sample size. This is because the significance threshold is typically predetermined (e.g., 0.05 or 0.10), and the effect size is decided by the treatment's effectiveness. Furthermore, the determination of any two of these elements completely establishes the third. Therefore, it is customary (and crucial) for researchers to utilize the significance level and expected impact size in order to calculate the necessary sample size to attain a specific power level. Prior to conducting a study, it is common to perform a priori power analysis as a component of research design [63]. So, the sample size estimation technique is well established.

Parameters	**Values**
Effect size	0.3
Statistical power level	0.9
Latent variables in the study	6
Observed variables in the study	32
Level of the probability	0.05
Minimum sample size to detect effect	200
Minimum sample size for model structure	123
Recommended minimum sample size	200

Table.1 – Priori Sample Size Estimation.

Within our structural model, the construct has a maximum of five arrows directed towards it. The number of latent variables is six. Under those six latent variables, there are thirty – two indicators or observed variables. The minimum absolute anticipated effect size for the structural equation model. By convention, values of 0.1, 0.3, and 0.5 are considered small, medium, and large respectively. Here, it is considered a medium effect (0.3). The desired statistical power level is 0.9 and the p-value is 0.05 significance level.

The outcome (Calculated by, [64]) says that the recommended minimum sample size is 200. Since we have obtained 220 valid responses, which satisfies the minimal sample size requirement.

9. Results of the Data Analysis

9.1. Reliability Rest: In the case of the reliability test, a well established statistical tool is Cronbach’s Alpha. It indicates how reliable the dataset is in a research. The value of Cronbach’s Alpha can be “0 < Cronbach’s Alpha < 1”. In this study, it is found that the Cronbach’s Alpha = 0.960. A commonly accepted guideline is that a Cronbach's alpha value of 0.70 or higher is considered good, 0.80 or higher is considered better, and 0.90 or higher is considered the best. With a Cronbach's Alpha score exceeding 0.90, our study is deemed to be of high quality and ready to proceed.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.960	.961	32

Table.2 – Reliability test.

9.2. Respondents Profile: The position of the respondents in their organization is shown in the table below. Out of the 220 respondents, most of them were Assistant Managers in position with the number of 25, which was 11.4% in comparison with the entire respondents. The number of Deputy Managers was close to the Assistant Manager, which was about 21 or 9.5%. Conversely, the Supply Chain Manager had the smallest representation among the responders, accounting for only 4.5%. The rest of the positions were pretty close to each other in number. Finally, it can be said that there was diversification in terms of respondents’ position in the collected data.

Position					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Assistant Manager	25	11.4	11.4	11.4
	Deputy Manager	21	9.5	9.5	20.9
	Industrial Engineer	22	10.0	10.0	30.9
	Intern Officer	14	6.4	6.4	37.3
	Maintenance Manager	15	6.8	6.8	44.1
	Production Manager	13	5.9	5.9	50.0
	Quality Control Officer	14	6.4	6.4	56.4
	Sales Manager	19	8.6	8.6	65.0
	Senior Assistant Manager	14	6.4	6.4	71.4
	Senior Commercial Officer	15	6.8	6.8	78.2
	Senior Manager	12	5.5	5.5	83.6
	Senior Product Executive	13	5.9	5.9	89.5
	Supply Chain Manager	10	4.5	4.5	94.1
	Territory Manager	13	5.9	5.9	100.0
	Total	220	100.0	100.0	

Table.3 – Position of the respondents in their organization.

Industry Types: Industry type indicates from which types of industry those data have been collected. In other words, the types of industries that have been included in the survey, from where the respondents belong. Table.3 delineates the summary from which types of industry the survey data has been gathered. Consumer Goods Manufacturers, Telecommunication, and Pharmaceuticals Industries were on top of the list with the numbers 34, 30, and 31 respectively. On the other hand, the Consumer Goods Industry was the least in number with a value of 10. One thing to clarify is that Consumer Goods Manufacturers are companies that produce tangible products intended for direct use by consumers. They are a subset of the broader consumer goods industry. The consumer goods industry encompasses not only manufacturers but also wholesalers, retailers, and various supply chain participants involved in the production, distribution, and sale of consumer products.

		Frequency	Percent	Valid Percent	Cumulative Percent
Industry_Type					
Valid	Ceramics Industry	18	8.2	8.2	8.2
	Construction Goods Manufacturer	29	13.2	13.2	21.4
	Consumer Goods Industry	10	4.5	4.5	25.9
	Consumer Goods Manufacturer	34	15.5	15.5	41.4
	Electronics Industry	13	5.9	5.9	47.3
	Garments Industry	21	9.5	9.5	56.8
	IT	34	15.5	15.5	72.3
	Pharmaceuticals Industry	31	14.1	14.1	86.4
	Telecommunication	30	13.6	13.6	100.0
	Total	220	100.0	100.0	

Table.4 – Industry types of the respondents.

Industry Size: We received a total of 220 answers from multiple organizations. In addition, we received a limited number of responses from a single company. Among the 220 responses, the medium-sized industry ranked first with a value of 102. The industrial, which was of considerable magnitude, was in close proximity to the medium-sized industry, with a numerical value of 98. Conversely, the survey revealed that the small-sized industry was likewise limited in quantity. We received a total of 20 replies from the small-sized industry, representing a percentage of no more than 9.1%. Regarding the determination of the industry's magnitude, we have examined the subsequent criteria. Small companies have a workforce of no more than 50 people, medium-sized companies have a workforce of 50 to 250 employees, and large companies have a workforce of more than 250 employees [6].

		Frequency	Percent	Valid Percent	Cumulative Percent
Industry_Size					
Valid	Large	98	44.5	44.5	44.5
	Medium	102	46.4	46.4	90.9
	Small	20	9.1	9.1	100.0
	Total	220	100.0	100.0	

Table.5 – Industry size.

In general, we can say that the respondents' sample appears to be varied, encompassing a range of industries, managerial roles, and levels of expertise. This dataset's diversity is demonstrated by the way it represents different industry sizes, managerial positions, and levels of knowledge. It reflects the diversity of the corporate scene by encompassing a wide range of industries, from "Large" enterprises to "Small" businesses. Furthermore, it provides a thorough understanding of the responsibilities and competencies of professionals within these businesses by incorporating data on various managerial positions and expertise levels. The dataset's diversity increases its relevance and usefulness for a variety of studies and insights.

9.3. Common Method and Nonresponse Bias: Common method bias is a statistical bias that can appear in research when same response method has been used in terms of both dependent and independent variable. Moreover, it can be a matter of concern when data is collected by using a self – report questionnaire. Common method bias can potentially impact the correlations between variables and lead to biased parameter estimates [65] is assessed by conducting an EFA. Harman's single-factor test entails the inclusion of all independent and dependent variables as inputs [66]. If one component accounts for the majority of the variability in all the indicators, then the data is characterized by a high level of common method variance (CMV). On the other hand, if multiple factors are identified as the main contributors to the communality, then the data has a low level of Common Method Variance (CMV). In simple words, all the factors are loaded under a single factor in Harman's single – factor test and the percentage of variance fall under 50% indicates that the common method bias is absent.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	14.912	46.600	46.600	14.912	46.600	46.600

Table.6 – Common Method Bias Analysis.

The research findings, as displayed in Table.5, indicate that the initial factor, which represents 46.60% of the total variance, falls below the 50% threshold. Therefore, there is no significant presence of CMV in the data.

In order to assess the existence of nonresponse bias, we administer a test by comparing two groups of respondents: an early group consisting of 50 individuals, and a late group also consisting of 50 individuals. The underlying assumption is that the early respondents are representative of the typical respondent, while the late respondents are representative of the average nonrespondent. [67]. The 32 indicators are assessed by doing a paired sample t-test to compare the two groups and no statistically significant differences have been found. Therefore, the overall research did not indicate a significant issue with nonresponse bias. However, it is important to be cautious when implementing the findings.

9.4. Exploratory Factor Analysis (EFA) on Business Analytics (BA) Applications: Business Analytics (BA) uses a variety of methods. We conduct an exploratory factor analysis (EFA) using principal component analysis with Varimax rotation (IBM, SPSS25) to gain insight into the characteristics of BA and to categorize different types of BA into appropriate groupings. Consequently, three (03) factors (Considered as BA_A, BA_B, and BA_C) are identified from 13 Business Analytics techniques (Table.08) with 68.246% of Total Variance Explained (Table.07).

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.181	47.547	47.547	6.181	47.547	47.547	3.182	24.476	24.476
2	1.487	11.436	58.983	1.487	11.436	58.983	3.080	23.695	48.171
3	1.204	9.264	**68.246**	1.204	9.264	**68.246**	2.610	20.075	**68.246**
4	1.088	8.371	76.617						
5	.792	6.094	82.712						
6	.636	4.889	87.600						
7	.436	3.355	90.955						
8	.357	2.747	93.702						
9	.287	2.211	95.913						
10	.226	1.735	97.648						
11	.161	1.241	98.889						
12	.112	.862	99.751						
13	.032	.249	100.000						

Extraction Method: Principal Component Analysis.

Table.7 – Exploratory Factor Analysis Using Principal Component Analysis with Varimax Rotation.

Rotated Component Matrix[a]			
	Component		
	BA_A	BA_B	BA_C
BA9	**.824**		
BA13	**.861**		
BA11	**.782**		
BA1		**.794**	
BA3		**.705**	
BA8		**.659**	
BA2	.538	**.628**	
BA5		**.609**	
BA7		**.557**	
BA12			**.804**
BA4			**.791**
BA6			**.646**
BA10	.544		**.549**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 6 iterations.

Table.8 – Components and Factor Loadings.

There were three components have been loaded under BA_A. Those BA9, BA13, and BA11 indicate Web Analytics, Data and Text Mining, and Interactive Data Visualization respectively. BA_B included six components in total. These are Statistical Analysis (BA1), Query and Analysis (BA3), Business Reporting and Dashboards (BA8), Forecasting (BA2), Optimization (BA5), and finally Simulation and Scenario Development (BA7). The last factor was considered as BA_C, which contains four components including BA12, BA4, BA6, and BA10 delineates Text, Audio, Video Analytics, Predictive Modeling, Model Management, and Social Media Analytics respectively.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.610**
Bartlett's Test of Sphericity	Approx. Chi-Square	2188.749
	df	78
	Sig.	**.000**

Table.9 – KMO and Bartlett's Test Result.

The threshold values recommended by [68] They are employed to assess the outcomes of EFA. The KMO (Kaiser – Meyer – Olkin) connected with the EFA has a value of 0.61, which indicates that the KMO Sampling Adequacy is greater than 0.60, making it acceptable. Bartlett's Test is statistically significant at a p-value of less than 0.000. Therefore, all of these factors demonstrate the suitability of the data.

9.5. Assessment of the Measurement Indicators of the Reflective Model: The PLS-SEM model we have incorporates both reflective and formative aspects. By adhering to the suggestion of [69], the reflective model is assessed by examining its internal consistency (Composite Reliability, CR), Indicator Reliability, Convergent Validity, and Discriminant Validity. Here, composite reliability measures the internal consistency of the analysis. And, AVE is the percentage of the contribution made by the variable. And, the expected value is 50%. For instance, BA_A, and BA_C has values over 0.5 or 50% (0.68, and 0.50 respectively). Though, BA_B is below 50%, it is close to 0.50.

Calculation of Composite Reliability (CR) and Average Variance Extracted (AVE)								
$CR = (\Sigma\lambda)^2 / ((\Sigma\lambda)^2 + \Sigma(1 - \lambda^2))$								
$AVE = \Sigma\lambda^2/n$								
Variables	**Indicators**	**Loading (λ)**	**Indicator Reliability (λ^2)**	**$1 - \lambda^2$**	**Cronbach's Alpha**	**Composite Reliability (CR)**	**AVE**	**√(AVE)**
BA_A	BA9	0.82	0.68	0.32	**0.881**	**0.86**	**0.68**	**0.82**
	BA13	0.86	0.74	0.26				
	BA11	0.78	0.61	0.39				
Summation (Σ)		2.47	2.03	0.97				
Variables	**Indicators**	**Loading (λ)**	**Indicator Reliability (λ^2)**	**$1 - \lambda^2$**	**Cronbach's Alpha**	**Composite Reliability (CR)**	**AVE**	**√(AVE)**
BA_B	BA1	0.79	0.63	0.37	**0.848**	**0.82**	**0.44**	**0.66**
	BA3	0.71	0.50	0.50				
	BA8	0.66	0.43	0.57				
	BA2	0.63	0.39	0.61				
	BA5	0.61	0.37	0.63				
	BA7	0.56	0.31	0.69				
Summation (Σ)		3.95	2.64	3.36				
Variables	**Indicators**	**Loading (λ)**	**Indicator Reliability (λ^2)**	**$1 - \lambda^2$**	**Cronbach's Alpha**	**Composite Reliability (CR)**	**AVE**	**√(AVE)**
BA_C	BA12	0.80	0.65	0.35	**0.776**	**0.79**	**0.50**	**0.71**
	BA4	0.79	0.63	0.37				
	BA6	0.65	0.42	0.58				
	BA10	0.55	0.30	0.70				
Summation (Σ)		2.79	1.99	2.01				

Table.10 – Convergent Validity and Internal Consistency Reliability Table.

Interconstruct Correlations			
	BA_A	**BA_B**	**BA_C**
BA_A	**0.82**		
BA_B	0.562**	**0.66**	
BA_C	0.549**	0.610**	**0.71**
** Correlation is significant at the 0.01 level (2-tailed).			

Table.11 – Interconstruct Correlation Analysis Table.

The findings derived from these constructs exhibit a high level of consistency, as indicated by the Composite Reliability scores presented in Table.10. The reason behind this is that all of the constructs satisfy the recommended reliability level, which is a value larger than 0.70 for Cronbach's Alpha and Composite Reliability.

First, we check each indicator's dependability by looking at its factor loadings and variance. The factor loadings should exceed 0.70, while the variance should be at least 0.50. With the exception of BA8, BA2, BA5, BA7, BA6, and BA10, all factor loadings exceeded 0.7. Four of the factor loadings among these six variables were nearly at the desired level. The remaining two are somewhat far but still adequate. Hence, the reliability of the indicator is not completely good, although it is generally adequate.

The convergent validity is deemed excellent as the Average Variance Extracted (AVE) value for each construct in Table.10 exceeds the recommended threshold value of 0.50, indicating a very good level of validity; except BA_B (0.44), which is very close to being the best but evidence also found that if AVE >= 0.40, but Composite Reliability > 0.6, the convergent validity of the construct will be acceptable [70], [71]. In this way, the construct BA_B in our study has AVE = 0.44. However, the Composite Reliability = 0.82. So, eventually, we can strongly say that in our study AVE value of the construct BA_B is also acceptable with the rest of the two constructs BA_A, and BA_C. The discriminant validity is deemed adequate according to two tests. Analyzing the Fornell-Larcker criterion is the initial test [52] To determine whether the square root of the average value (AVE) for each construct is higher than the correlation between the construct and any other construct, as indicated by the comparison summarized in Table.11.

The next test is to determine whether individual indicator exhibits the highest level of association with the construct it is linked to which is true as well according to Table.12. Demonstrates that there is satisfactory discriminant validity.

Cross-Loading Analysis[a]

	Component		
	BA_A	BA_B	BA_C
BA13	**.861**	.121	.089
BA9	**.824**	.195	.313
BA11	**.782**	.259	.187
BA1	.244	**.794**	.099
BA3	.332	**.705**	.292
BA8	-.168	**.659**	.137
BA2	.538	**.628**	.035
BA5	.278	**.609**	.373
BA7	.457	**.557**	.474
BA12	.128	.125	**.804**
BA4	.137	.308	**.791**
BA6	.213	.453	**.646**
BA10	.544	-.090	**.549**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 6 iterations.

Table.12 – Results of Cross-Loading Analysis.

9.6. Assessment of the Formative Model Measurement Indicators: The formative measurement model is evaluated in terms of collinearity, the indicator weights, the significance of weights, and the indicator loadings [56]. To assess the level of collinearity, the variance inflation of factor (VIF) values of all formative constructs is evaluated in Table.13. The threshold value suggested for VIF is 3.3 by [59] and 5 by [56]. However, evidence has found that if the value of VIF is between 1 – 5 indicates a "Moderate Correlation" between variables. It quantifies how closely the independent variables are related to one another. In our study, DDE3 was very close to 5, and all other values are in-between 1 – 5. And, in terms of Tolerance value, the range between 0.1 to 0.2 indicates multicollinearity issue [72]. However, all the tolerance values are greater than 0.20 except DDE3 (0.19) is close to 0.2. It can be negligible. So, it can be said that there are no collinearity issues. Here to mention that collinearity issue can enhance the variance or standard error of calculated coefficient.

Construct	Indicators	Collinearity Statistics	
		Tolerance	VIF Value
BA	BA_A	0.62	1.62
	BA_B	0.56	1.80
	BA_B	0.57	1.77
DDE	DDE1	0.21	4.84
	DDE2	0.27	3.74
	DDE3	0.19	5.27
	DDE4	0.30	3.29
	DDE5	0.26	3.87
IPC	IPC1	0.29	3.48
	IPC2	0.21	4.81
	IPC3	0.26	3.89
	IPC4	0.24	4.20
DDM	DDM1	0.57	1.75
	DDM2	0.53	1.89
	DDM3	0.48	2.09
	DDM4	0.69	1.45
DME	DME1	0.28	3.53
	DME2	0.25	4.07
	DME3	0.50	2.00
SDME	SDME1	0.31	3.25
	SDME2	0.33	3.03
	SDME3	0.36	2.75

Table.13 - Collinearity Assessment Analysis.

9.7. Outer Weights and Significance Testing: Outer weights of an indicator describes how is the relation between it and under which construct the indicator is. In this way, outer loading shows the contribution of an indicator to the particular construct, under which the indicator lies. And outer loading becomes a matter of analysis, when the value of outer weights is not significant depending on the p value (Less than 0.05, to be significant) is described below. The bootstrapping technique, which involved 5,000 samples, was used to evaluate, and summarize the outer loadings, outer weights, and associated significance testing p-values of all formative indicators. The results are presented in Table.14. Except BA_C, DDE3, DDE5, DDM4, DME1, DME2, and SDME2 all other indicators' outer weights are significant by considering the p–value. But there is something more to be considered. When the outer weight of a formative indication is not statistically significant, [69] Recommends retaining it if its outer loading exceeds the value 0.5. Since all the suspected indicators have an outer loading larger than 0.5, except for DDM4, they are maintained. This demonstrates the absolute contribution of each indicator to the related formative construct. The DDM4 is not worth keeping. BA_C, DDE3, DDE5, DME1, DME2, and SDME2 are regarded as important indications in the study.

Formative Constructs	Formative Indicators	Outer Weights	p - Value	Outer Loadings
BA	BA_A	0.4700	0.000	0.8510
	BA_B	0.5890	0.000	0.9090
	BA_C	0.0910	**0.505**	0.7080
DDE	DDE1	-0.5580	0.000	0.6530
	DDE2	0.7320	0.000	0.8530
	DDE3	-0.0090	**0.949**	0.7380
	DDE4	0.8070	0.000	0.9160
	DDE5	0.0110	**0.915**	0.7730
IPC	IPC1	0.1120	0.068	0.8390
	IPC2	0.1880	0.007	0.9030
	IPC3	0.1700	0.007	0.9010
	IPC4	0.5980	0.000	0.9760
DDM	DDM1	0.9090	0.000	0.9660
	DDM2	0.3400	0.000	0.6500
	DDM3	-0.1230	0.034	0.6370
	DDM4	-0.0460	**0.300**	**0.4440**
DME	**DME1**	0.0700	**0.595**	0.6190
	DME2	-0.1610	**0.159**	0.6460
	DME3	1.0600	0.000	0.9970
SDME	SDME1	0.3340	0.003	0.9020
	SDME2	0.1210	**0.384**	0.8450
	SDME3	0.6180	0.000	0.9640

Table.14 – Test Results of Outer Weights, Outer Loadings, and P – value.

9.8. Hypothesis Testing: SmartPLS 4 is utilized for hypothesis testing, and the outcomes (Path Coefficient, P-value, and R^2 value within the latent constructs' circle) are displayed in Figure.02 below. Following [56], in order to assess the structural model, it is necessary to examine the model's interactions for collinearity, significance, and relevance. The SmartPLS 4 software was utilized to assess collinearity concerns. The VIF values are displayed in Table.15, and no collinearity problem has been identified. Since all the values fall within the range of 1 to 5, it may be concluded that there is no evidence of collinearity.

Collinearity Assessment						
	BA	**DDE**	**DDM**	**DME**	**IPC**	**SDME**
BA		1			1.579	
DDE			1.893		1.579	
DDM				4.222		2.735
DME						2.735
IPC			1.893	4.222		
SDME						

Table.15 – Collinearity Assessment Table.

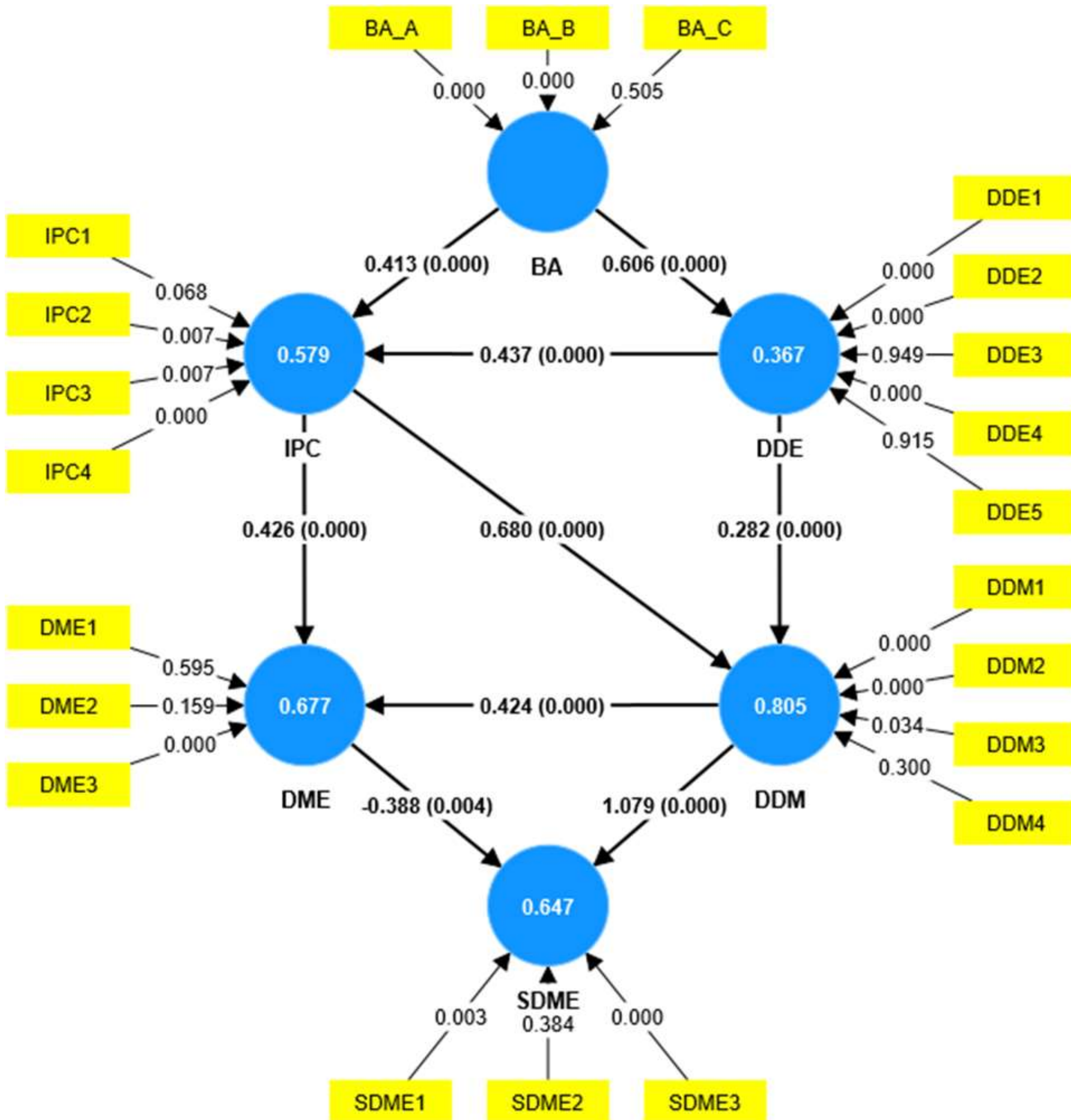

Figure.2 – Research Model and Path Analysis.

The relevance and significance of path coefficients are illustrated in Figure 02. BA has connections to both DDE and IPC. DDE has a robust correlation with IPC, which is substantially correlated with DDM and DME. On the other hand, DME is not contributing to SDME, while DDM created the most significant impact or contribution on SDME.

DDM has the most pronounced overall impact on SDME, as shown in Table 16. This is followed by BA, DDE, and IPC. IPC influences DME significantly. In addition to this, BA performs a significant impact on both DDE and DDM. The remaining data in the table illustrates that there are moderating effects among all the constructs.

Total Effect on SDME						
	BA	DDE	DDM	DME	IPC	SDME
BA		0.606	0.631	0.556	0.677	**0.465**
DDE			0.579	0.432	0.437	**0.457**
DDM				0.424		**0.914**
DME						**-0.388**
IPC			0.68	0.715		**0.456**
SDME						

Table.16 – Total Effect Assessment on SDME.

Here, in Table.17, R^2 values illustrating the predictive power or how capable the research model is to predict accurately. In this way, Q^2 value derives the predictive relevance of the research model.

	R^2 Value	Q^2 Value
DDE	0.367	0.346
DDM	0.805	0.471
DME	0.677	0.454
IPC	0.579	0.439
SDME	0.647	0.382

Table.17 – Result of R^2 and Q^2 Values.

The model's predictive relevance with respect to the latent variables is supported by the fact that all of the Q^2 values in Table.16 are greater than zero [56]. The R^2 values of the variables represent the model's predictive power. The recommended effect sizes for R^2 while using PLS-SEM in IT research are small (0.1), medium (0.25), and big (0.36) [53]. Table.17 shows that all of the values are more than 0.36. Additionally, data shows that an appropriate R^2value falls somewhere between 0.5 and 0.99. Every single construction, with the exception of DDE, rests somewhere in the range and is backed by [53]. So, R^2 and Q^2 values are also satisfactory.

The results of the hypothesis testing are summarized in Table.18, along with the statistically significant p-values and standardized path coefficients where applicable.

Hypothesis	Hypothesized Path	Path Coefficient	P - values	Hypothesis Test
H1	BA -> IPC	0.413	0.000***	Supported
H2	BA -> DDE -> IPC			Supported
H3	IPC -> DDM	0.68	0.000***	Supported
H4	IPC -> DME	0.426	0.000***	Supported
H5	DDE -> DDM	0.282	0.000***	Supported
H6	DDM -> DME	0.424	0.000***	Supported
H7	DDM -> SDME	1.079	0.004**	Supported
H8	DME -> SDME	-0.388	0.000***	Omitted
$^{***}p < 0.001$, $p^{**} < 0.01$				

Table.18 – Summary of the Established Hypothesis.

"H1: Business analytics directly and favorably impacts Information Processing Capability.", which is supported as Business Analytics' influence on IPC is 0.413 (p value < 0.001).

Mediating Role of DDE Calculation By Using VAF (Variance Accounted For)	
Let,	
1	BA
2	DDE
3	IPC
Formula of VAF = $(P_{12} * P_{23}) / (P_{12} * P_{23} + P_{13})$	
P_{12}	0.606***
P_{23}	0.437***
P_{13}	0.413***
Hypothesis	H2
Indirect Effect	0.2648***
Total Effect	0.6778***
VAF	**39% (Partial Mediation)**
VAF Ranges	**Type of Mediation**
If, VAF < 20%	No Mediation
If, VAF 20 - 80%	Partial Mediation
IF, VAF > 80%	Full Mediation
Significance Level	**$^{***}p < 0.002$**
Decision	**Partial Mediation is Observed.**

Table.19 - Mediating Role of DDE Calculation By Using VAF (Variance Accounted For).

“*H2: Through the arbitration of a Data-Driven Environment, Business Analytics has an advantageous and indirect impact on Information Processing Capabilities.”*, In order to determine whether or not it is true, the role that DDE plays as a mediator in the connection between BA and IPC is examined in Table.19. applying the procedures that were advised by [73] bootstrapping [56]. Finding the variance accounted for (VAF) tells us how large the mediating effect is in relation to the other effects [74]. The analysis results are shown in Table.19. The table shows that DDE partially (39%, Partial Mediation) though it acts as a powerful mediator between BA and IPC, which supported hypothesis 2.

“*H3: IPC positively influences DDM.*”. Table.18 shows that IPC has an impact of 0.68 on DDM (p value < 0.001); thus, H3 is supported.

H4 indicates “*H4: IPC has a direct and favorable impact on DME.*”, this is confirmed by the fact that the effect value of IPC on DME is 0.426 (p value < 0.001).

H5 proposes “*H5: DDE certainly manipulates DDM.*”, it is also supported by the analysis. As the Table.18 shows the effect value is 0.282 (p value < 0.001).

In terms of H6, “*H6: DDM is favorably amalgamated with DME*”. In terms of DDM's effect on DME, the value is 0.424. (p value < 0.001), which confirms that Hypothesis 6 (H6) is also supported according to the analysis.

H7 indicates “*H7: DDM positively influences SDME.*”. According to the hypothesis analysis in Table.18, the effect of DDM is greater than any other constructs in the research with the value of 1.079 (p value < 0.01) confirming that H7 is also supported.

In our last and final Hypothesis, “*H8: DME might favorably manipulate SDME.*” It is suspected that DME could have a significant impact on SDME. However, the negative result was probable. As we mentioned before, while establishing the hypothesis “Effective decision-making, however, does not ensure success as a result of that ambiguity. Many elements could be at play in this situation.”. After analysis, we found that DME has a significant impact on SDME (p value < 0.001). However, the path coefficient value is negative (-0.388), which is not acceptable. So, the hypothesis should be omitted.

10. Findings of the Research: After reviewing the data, we can confidently state that each of the structures plays a key role in setting up good decision-making. The research shows that among these dimensions, Data-Driven Decision-Making (DDM) is the most important in improving successful corporate decision-making and ultimately leading to Successful Decision-Making Effectiveness (SDME). According to previously discussed literature we know that data is the key to establishing difference between organizational success and failure. In this process, the research also establishes the statement that Data – Driven Decision – Making plays the most significant role, while effective decision making is highly required in todays’ competitive business analytics world.

11. Discussion on the Study: The objective of this study is to gain a deeper comprehension of the mechanisms via which BA promotes SDME. BA has recently regained significance as a prominent field of study [60], [75], due to the limited amount of scholarly study conducted on the impact of BA on organizational decision-making, our understanding of this topic remains limited. [76], [77].

This study constructs a path model to conceive and examine relevant ideas associated with business analytics (BA) and its influence on sustainable development and environmental management (SDME). Preexisting BA literature, the information processing viewpoint, and contingency theory provide the groundwork for this. Our study offers unique perspectives on how Business Analytics improves the effectiveness of decision-making, while also enhancing our understanding of these concepts and their interrelationships.

Initially, We contribute to the existing knowledge on business administration by clarifying the methods via which business administration promotes strategic decision-making effectiveness. Prior studies have indicated the need of establishing a Digital Data Ecosystem (DDE) and the potential for utilizing Business Analytics (BA) to provide value for businesses [17], [20], [19], these claims are not well supported by conceptual understanding or actual data. By creating a conceptual understanding supported by pertinent theories and offering empirical data, this research expands our comprehension. Our research highlights the intricate interdependencies between various organizational elements and the processes that underlie BA applications by conceptualizing the connections between BA and SDME. Additionally, we have offered actual data to back up our idea. The research results indicate that BA has a beneficial impact on IPC, both directly also indirectly, by means of DDE acting as a mediator. IPC will have a beneficial impact on DDM, leading to a subsequent improvement in both DME and SDME. This finding validates the assertions made in previous studies that BA has a favorable impact on IPC. Moreover, the findings indicate that BA not only has a direct impact but also positively influences DDE [17], [20], [19]. Our research reveals that in order for an organization to effectively utilize Business Analytics (BA), a Decision-making and Data-driven Environment (DDE) must simultaneously facilitate and empower BA activities. Without this support, it is probable that BA applications will not be effective. To improve our understanding of the topic, we believe that exploring the relationships between BA and other organizational qualities will stimulate further study efforts.

Secondly, we contribute to the ongoing discussion over the proposition that IT can have a substantial impact on shaping organizational attributes supported by contingency theory for example, [78], [79]. Our empirical data indicates that organizations will become aware of the benefits of developing a suitable strategy, structure, and procedures to direct and facilitate business analytics (BA) activities when they confront the challenges posed by big data, growing competition, and technological advancement. Hence, a significant implication of the study is the necessity for further investigation into how Business Analytics (BA) facilitates an organization's decision-making process by aiding in the creation of a Decision-making Decision Environment (DDE).

Thirdly, we improve the information processing perspective by offering actual data that supports the central concept that an organization must strategically design its structure and business processes to enhance its information processing capacity, hence enhancing its decision-making capabilities. [10] [13], [15]. Our research indicates that improving an organization's IPC (Information Processing Capability) can improve decision-making by implementing certain strategies, policies, structures, and processes to support Business Analysis (BA) activities. This is backed by real-world examples and the idea of a DDE. Based on the processing view of information, our research shows that putting in place a DDE will help an organization's IPC and, in turn, its DME and SDME. This supports the idea that BA is a key factor in the creation of a DDE, which is based on the theory of contingencies. Consequently, research that employs the information processing view and is grounded in contingency theory enhances our understanding of how BA impacts decision-making.

The results of our study have significant ramifications for BA practitioners as well. According to the results, an organization's BA is a significant factor in determining its DDE, which is a prerequisite for using BA effectively and making decisions. Therefore, to fully utilize BA, a DDE must be developed concurrently with its implementation. A DDE would strengthen the effect of the BA on the IPC of the company, which affects DDM, DME, and SDME. As a result, businesses should concentrate on creating IPC with BA apps in an environment where data is king.

12. Limitations of the Study: The study includes several restrictions. Firstly, even though we developed formative constructs by the four decision rules [59] to prevent misspecifications, the research design might not capture the essence of all six formative constructs. Consequently, we can't check if the indicators we choose cover all of the formative constructs' domains by evaluating their convergent validity.

Secondly, small businesses with fewer than 50 employees are not included in our sample. Our conclusions therefore do not apply to small businesses.

Thirdly, although quantitative measurements based on particular choices may supplement the perceived measures, in order to gain a clearer picture of the study's important components, we employed perceived measurements.

Moreover, business processes, and distribution of underlying data are typically assumed in business analytics models. Modifications to these presumptions could affect the models' applicability and accuracy. The generalizability of findings across various industries or business environments may be restricted due to sensitivity to assumptions. The proficiency of the people evaluating and using the findings determines how effective business analytics will be. Decision-makers with a weak grasp of analytics run the risk of misinterpreting the data or choosing the wrong course of action. Decisions made with analytics may not work as well when people make them because of cognitive errors and how they act as decision makers.

Lastly, We have not tested IPC homogeneity since we have not been able to find a suitable instrumental variable for these components.

13. Conclusion: Even with these problems, we think that our work opens up new areas to explore in the future. To enhance comprehension of BA and its impacts, doing more targeted research can contribute to the improvement of investment decision-making for firms. Subsequent research endeavors could investigate the current condition of business analytics (BA) software and their impact on decision-making processes inside small enterprises. Furthermore, it is important to carry out additional business analysis research on the influence of factors such as the business environment, organizational structure, and top management team on the outcomes of strategic decisions. In summary, business analytics is crucial for enhancing the efficacy of decision-making in enterprises. Employing data-driven insights allows companies to optimize operations, enhance decision-making, and adapt to dynamic market situations. Leaders with the ability to get crucial insights from data are more adept at identifying opportunities, mitigating risks, and strategically allocating resources. Integrating analytics into decision-making processes is crucial for achieving sustainable growth and gaining a competitive edge in the fast-paced corporate landscape of today. This is especially important as technology and analytical tools continue to advance. The synergy between business analytics and effective decision-making is crucial for achieving success in the modern corporate landscape.

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15. Appendix:

Questionnaire

Constructs	Indicators	Symbols
	How Often Does Your Organization Use The Following:	
BA(Business Analytics)	Statistical Analysis	BA1
	Forecasting	BA2
	Query and Analysis	BA3
	Predictive Modeling	BA4
	Optimization	BA5
	Model Management	BA6
	Simulation and Scenario Development	BA7
	Business Reporting/Dashboards	BA8
	Web Analytics	BA9
	Social Media Analytics	BA10
	Interactive Data Visualization	BA11
	Text, Audio, Video Analytics	BA12
	Data and Text Mining	BA13
DDE (Data Driven Environment)	We have an explicit organizational strategy that guides business analytics activities	DDE1
	We have explicit policies and rules that guide business analytics activities	DDE2
	We have a well-defined organizational structure that enables business analytics activities	DDE3
	Business analytics is integrated into our business processes	DDE4
	We prioritize major business analytics investments by the expected impact on business performance	DDE5
IPC (Information Processing Capability)	We are more effective than our competitors at;	
	Capturing Data/Information	IPC1
	Integrating Data/Information	IPC2
	Analyzing Data/Information	IPC3
	Using Insights Gained From Data/Information	IPC4
DDM (Data Driven Decision Making)	We use data-based insight for the creation of new services/product	DDM1
	We depend on data-based insights for decision-making	DDM2
	We are open to new ideas that challenge current practice based on data-driven insight	DDM3
	We have the data to make decisions	DDM4
DME (Decision Making Effectiveness)	We are more effective than our competitors at;	
	Responding quickly to change	DME1
	Making real-time decisions	DME2
	Understanding customers	DME3
SDME (Success on Decision-Making Effectiveness)	Making decisions has become easier and the insights from business analytics	SDME1
	Success in making risky decisions has increased	SDME2
	Business analytics insights helped to stand uniquely in the market.	SDME3

The End