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The Influence of a Data-Driven Culture on Product Development and Organizational Success through the Use of Business Analytics

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Abstract

A Data-Driven Culture (DDC) is believed to facilitate a business-focused cultural shift inside a company. Providing considerable returns to the businesses' goods and procedures breakthroughs is evaluated. Several companies have started using various sophisticated technology-integrated Business Analytics (BA) technologies to enhance their company performance. The progress in information and communication technologies has enabled companies to consider using BA solutions, including Artificial Intelligence (AI). This has significantly transformed companies' business-focused cultural environments, allowing them to make precise decisions to enhance their creativity and performance. This research examines the influence of a company's DDC on procedure efficiency and product development, which leads to improved overall company outcomes and increased business value. Using a systematic approach, developing a theoretical framework and a collection of hypotheses is first supported by existing research and insights from the resource-based perspective and adaptive capacity concept, specifically in the company's environment. These findings are then statistically verified using a survey that includes 513 genuine replies from workers of various firms utilizing business analytics tools equipped with AI capabilities. The results indicate that fostering a DDC inside an organization has a significant impact on goods development as well as procedure improvement. It improves business worth by enhancing overall efficiency.

Keywords: Business Analytics, Data-Driven Culture, Product Development, Organizational Success.

1 Introduction to Business Analytics

Businesses from a wide range of regions, industries, and kinds continually adapt their strategies and processes to adapt efficiently and appropriately (Naradda Gamage et al., 2020). This is because the business environment is always changing and is very competitive. Conventional approaches and concepts are no longer effective in effectively handling the issue (Bunkangsang et al., 2022). To fulfill the present requirements and be ready for the future, firms are adopting more appropriate and forward-

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thinking strategies. When considering this specific scenario, the unavoidable and irreversible potential of Business Analytics (BA), which is accelerated and assisted by fast digitalization and encouraged by a culture that is reliant on data, appears as an essential component for optimizing organizational performance and raising the value of the company (Akter et al., 2022). Big Data Analytics (BDA) is a methodical process that involves collecting and analyzing data to derive important insights that can be used to improve the value of a company and create a competitive advantage (Ranjan & Foropon, 2021; Arora., 2024).

Companies are being forced to handle the ever-changing demands and requirements of their prospective consumers due to the dynamic character of the global economy. This is especially true about the opportunities for product innovation and development. To do this, businesses need to collect various customer data (Imam et al., 2022). Within this scenario, the Corporate Data-Driven Culture (DDC) has emerged as an essential catalyst for boosting innovation, performance, and economic value (Chaudhuri et al., 2021; Merin et al., 2023; Ribalta et al., 2021). When it comes to addressing the growing challenges linked with business innovation, companies need to rely on sophisticated data science approaches and use a variety of tools to analyze the data they collect (Fernando et al., 2024). It has been shown that adopting a culture driven by data has a substantial impact on both the efficiency of operations and the capacity of businesses to reinvent their goods (Buljubasic., 2020). The term "culture" refers to a collection of beliefs, methods, and qualities per the principles that are best for building automation technology (Fosso Wamba et al., 2024; Asadov et al., 2018; Abdullah., 2020; Obeidat et al., 2023; Bobir et al., 2024).

Businesses can become more data-driven via business analytics, making them need to review enormous volumes of customer records. Recognizing the relevance of information technology and data science is required before this can be accomplished (Padmanabhan et al., 2019). A Business Analysis (BA) is a technique and a set of abilities. An organization's performance in collecting resources that contribute to effective business planning may be evaluated using a method known as BA (Niu et al., 2021; Knezevic et al., 2018). It is vital to conduct a statistical analysis of the big data that is accessible to improve the firm's performance and satisfy the customers' expectations. This study will also help improve product innovation, which is another benefit. Data assessment necessitates professional data analysis abilities, the use of relevant intelligent technology, and the installation of good governance (Ashaari et al., 2021). A DDC is defined as a collection of qualities and practices embraced by a group of persons who feel that the acquisition, interpretation, and use of certain sorts of materials and information are crucial for the success of businesses.

An apparent gap in existing research is seen in two different ways. The issue has been examined without adequately considering the essence or the scope of the DDC function in the context of BA (Thanabalan et al., 2024). The need for more comprehension of the correlation between organizational environmental monitoring and business process efficiency and product innovation highlights the pressing need for further study in this field. The issue of corporate DDC still needs to be explored. To address this apparent discrepancy, the study examines the influence of a company's DDC on process efficiency and new product development, which contributes to improved overall efficiency and, eventually, more excellent commercial value.

2 Background and Analysis

BA has been elucidated via several perspectives. There currently needs to be a universally recognized definition of BA. Within the scope of this research, BA is defined as the utilization of information, analytical and qualitative assessment, descriptive and forecasting methods, and fact-depending managing models to inform and guide decision-making and actions. The results of the research have shown that BA is considered to be an approach that is based on evidence and facts to guide decision-making (Yalcin et al., 2022). The decision-making process inside an organization is aligned with a DDC based on the established patterns of attitudes, habits, and practices. One definition of a DDC is a collection of characteristics and practices embraced by persons who have a firm conviction that the acquisition, understanding, and use of certain kinds of materials and techniques are necessary for the success of their businesses (Hashim et al., 2024). This characterization is consistent with the culture of the company. The concept of a DDC has been investigated by several academics, who have defined it as a culture that operates based on factual information and emphasizes data analysis. According to research, a firm must use BA to improve its DDC processes to get a competitive advantage (Chatterjee et al., 2024). This activity can potentially increase the firm's profitability by enabling the organization to make accurate decisions based on data-driven insights (Kutlu et al., 2021).

According to the research findings, for a company to be able to detect and respond to the needs of external markets successfully, the organization must be able to scan and assess its business environment. This will enhance the firm's ability to innovate in both its processes and products. Studies have concluded that information is a crucial asset for a company in improving its operations and advancing its goods via innovation (Azeem et al., 2021). Studies have expressed that in addition to using technology, a company's management must effectively handle the information to get an edge over their rivals. The firm's capacity to get precise information from suitable sources and analyze the ecosystem enables it to enhance its ability to create. This eventually enhances the company's ability to get a competitive edge. It is undeniable that strengthening a company’s capacity for innovation leads to improved performance. However, to get optimal outcomes, the firm's assistance from the administration acts as a crucial role. Previous research shows that more backing from upper-level executives is needed to ensure a company's ability to enhance its performance (Liu et al., 2022). Multiple studies have emphasized that leadership backing is linked to promoting knowledge-sharing activities across various organizations. Research has shown that BA significantly influences a company's capacity to innovate, be productive, and create value (Oesterreich et al., 2022). More research needs to examine the role of BA in fostering a DDC and its effect on developing creative capabilities.

Various studies emphasize the impact of organizations' capacity to effectively analyze data on enhancing company performance by developing suitable BA strategies (Fuertes et al., 2020). Accurate data analysis is necessary, and research has emphasized the ability of BA tools to evaluate information in the food sector. Implementing a DDC will enhance the effectiveness of various marketing companies by transforming managers into accomplished decision-makers who rely on information. Multiple studies have examined the effect of BA on strategic business procedures and the contributions of data science to business enterprises (Bordeleau et al., 2020). All of these studies highlighted the efficacy of a DDC. Still, they should have paid more attention to how such a culture influences organizations' ability to innovate in terms of their goods and procedures to enhance outcomes and remain competitive in a rapidly changing market.

3 Data-driven Culture on Product Development and Organizational Success with BA

The study is primarily exploratory since it examines problems needing more precise definitions. This research analyzes the effect of BA on product development and process performance and how a DDC within a company can enhance its business value. These issues have yet to be clearly defined in previous research. In addition, this study addresses inquiries about the "what" and "how" aspects (objectives 1 and 3 of the research) that are primarily associated with exploratory research.

The research used respondents' comments obtained via a survey. The appropriateness of using a Partial Least Squares Structural Equation Modeling (PLS-SEM) was acknowledged. PLS-SEM is especially favored when there is a scarcity of existing theory, it isn't easy to define the model accurately, and the data does not follow a normal distribution. The PLS-SEM approach is advantageous for obtaining improved outcomes in an exploratory investigation such as this. PLS-SEM was considered more suitable due to the prerequisites, such as a sufficient sample size, data with a normal distribution, and an adequately specified system. These prerequisites involve selecting suitable parameters and establishing their connections to transform a theory into a Structural Equation Model (SEM). The software used for this study was Smart PLS 2.0. A conceptual method is constructed and represented in Figure 1 using the above inputs.

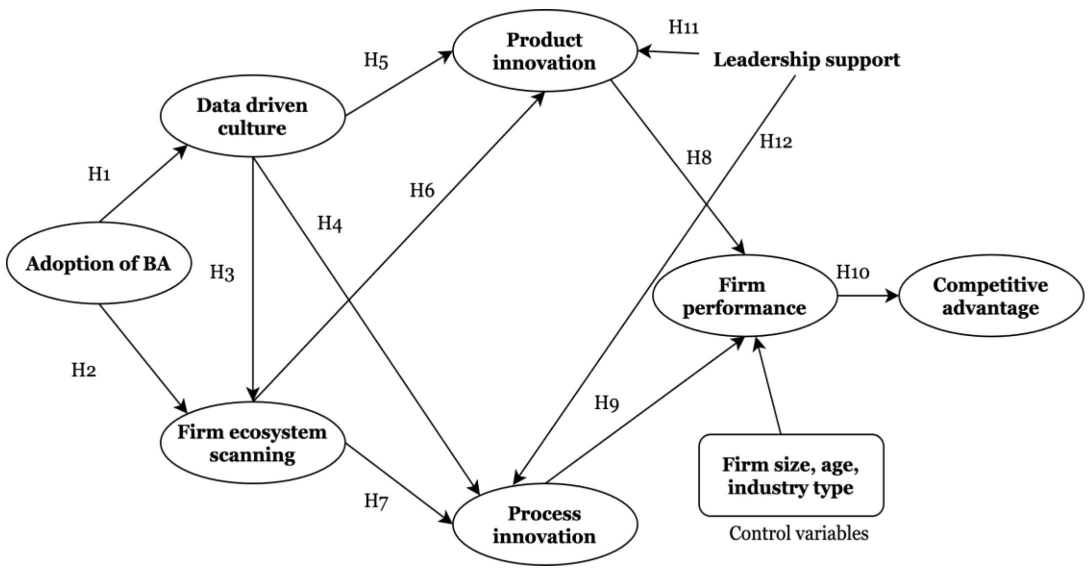

Figure 1: Conceptual Model

Research Tools

Examination of existing analysis, analysis of conceptual agreements, and use of methods were essential in developing the research tools to assess the data verification of the conceptions. The tools underwent several correction operations, resulting in the preparation of 31 items. Several domain experts were requested to evaluate the items in this research, and any issues related to readability that they identified were addressed to enhance the comprehensiveness of the questions. The 31 research tools were formulated as statements. The feedback was quantified for analysis using a five-level Likert scale. The preference was given to a seven-level Likert scale over a five-level Likert scale due to the more minor differences in magnitude between the choices on the 7-point scale.

The current research focuses on BA in the DDC context, which is considered both intricate and novel. If the seven-level scale had been utilized, it posed a challenge for the participants to differentiate between the closely related options such as 'Strongly Disagree' and 'Disagree' or 'Agree' and 'Strongly Agree.' This difficulty arises due to the similarity of these options and the inherent complexity of the subject matter, compounded by the topic's novelty. The instruments were formatted as statements, with responders providing five possibilities. The five alternatives span from Strongly Disagreed (SD), denoted as 1, to Strongly Agreed (SA), denoted as 5.

Data Collection

A diverse range of firms was collected from the Bombay Stock Exchange, including different sizes, ages, and sorts. This research requires comments from participants who are knowledgeable about data-driven culture and BA's potential to enhance a company's business values, with a focus on their environmental scanning skills. Objective sampling is successful when academics can rely on their judgment to choose particular participants. Therefore, the Bombay Stock Exchange has been used to get the list of companies. An analogous approach to data collecting has also been used in another investigation. The companies' names were selected from the Bombay Stock Exchange for convenience. The data collection in this research was conducted using purposive and convenient sampling methods. Many companies listed on the Bombay Stock Exchange were excluded due to needing to satisfy the requirements. However, it is feasible to choose 168 businesses.

The sample consisted of many product-oriented enterprises to provide high external reliability and generalizability. The study focused on selecting large and medium-sized enterprises since it was found that small industries had yet to use BA technologies owing to limited resources. Efforts were first made to reach out to personnel of various hierarchies within these 156 companies; however, the majority of the companies were unwilling to respond. After encountering these obstacles, it managed to get a representative sample of 28 firms. One thousand two hundred seventeen people, spanning various hierarchical levels and roles, willingly responded to the 31-question survey. It sent a request via email to these 1218 workers, asking them to provide their comments within three months. To increase the rate at which people reply, it communicated to the possible participants that the purpose of this research is only for academic purposes. The research reassured the participants that their identities and personal information would be kept entirely secret. Four hundred fifty-six responses were received within the specified timeframe, resulting in a response rate of 42.7%. The outcomes are discussed in Table 1.

Table 1: Demographic Analysis (N = 456)

Features	Details	Data	Result (%)
Business model	Services	142	31.14
	Manufacturing	314	68.86
Company size	Small (< 150 workers)	10	2.19
	Medium (150—500 workers)	230	50.44
	Large (>500 workers)	216	47.37
Company Age	Less than 5 years	100	21.93
	5—12 years	191	41.89
	Above 12 years	165	36.18
Gender	Men	286	62.72
	Women	170	37.28
Designation	Executives	100	21.93
	Senior managers	146	32.02
	Mid-level managers	210	46.05

Survey-based tools raise concerns about non-response bias in the information gathered. Two methods have been used to perform the non-response bias assessment. Initially, a performance bias test has been carried out. The researchers performed paired sample t-tests to compare the participating companies' Return On Assets (ROA) with the corresponding median values. A positive correlation coefficient of more than 0.43 was established among the ROAs. Chi-square examination and separate t-tests were conducted on the first and final hundred replies. The evaluation indicated no significant variation ($p < 0.05$), indicating that non-response bias did not affect the responses. Out of the total number of replies, precisely 19 needed to be completed. The research was analyzed on the remaining 435 complete responses.

Implications for Practice

This research offers valuable insights to business analytics professionals and organizational managers for enhancing company outcomes. This research emphasizes the need for leaders of businesses to focus on developing a culture that relies on data to enhance workers' understanding and knowledge. Implementing a DDC would enable stakeholders to prioritize data quality to improve the effectiveness of business analytics and the organization's capacity to scan its surroundings. Ultimately, this would enhance the organization's innovative products and commercial success.

The research has furnished managers with many results and viewpoints for contemplation. Implementing BA tools in the workplace does not inherently lead to generating new ideas for enhancing a company's process and product development within the framework of DDC characteristics. Business analysts working on the technical aspect must communicate their conclusions and the constraints of their study to the relevant workers. The organization should provide comprehensive training to all personnel involved in innovation about using BA. Companies might provide "self-service" business analytics tools to teach other workers how to analyze data. They can actively promote and acknowledge employees' efforts. Additional measures should be taken to enhance the company's data scanning power to obtain valuable information from various related assets. The DDC perspective has reinforced the concept.

Within the digital company, the BA method relies on data to make informed decisions. However, not every data provide beneficial inputs. Therefore, while improving their capacity to scan data, firms' executives should ensure that staff are knowledgeable of carefully selected, unique, and irrefutable facts. Employees tasked with data acquisition should possess a high level of proficiency in this matter. Organizational managers enhance their response to the ever-changing foreign marketplaces by utilizing business analytics solutions to create more sophisticated business information. This would also facilitate the organization's innovative product efforts by creating valuable and relevant consumer offerings.

4 Results and Discussion

Data Evaluation

The measuring system was evaluated by calculating each item's loading factor (LF) and then determining its converging validity. The compositing reliability (CR), averaged variation extraction (AVE), variability inflating factor (VIF), DDC, leadership support (LS), and Cronbach's alpha (α) were used to measure internal consistency, reliability, multicollinearity, and construction consistency correspondingly. Every factor (Applied Behavior Analysis (A-B-A), DDC, Field Emission Scanning (F-E-S), Point of Interest (P-O-I), Public Radio International (P-R-I), Financial Planner (F-P), Certified Management Accountant (C-M-A), and Audio-Visual Aids (A-V-A)) was determined to be within the permissible range, proving the products' reliability. The constructions are deemed legitimate if they exhibit internal consistency and lack any multicollinearity faults.

Discriminant Verification Assessment

The estimation indicates that every square root of the models' averaged variation extractions is higher than their corresponding correlation factors. The Fornell and Larcker criteria are satisfied, confirming the validity of discrimination. The outcomes are discussed in Table 2.

Table 2: Validity Testing Result Analysis

Model	A-B-A	DDC	F-E-S	P-O-I	P-R-I	F-P	C-M-A	A-V-A
A-B-A	0.93							0.8
DDC	-0.12	0.94						0.95
F-E-S	0.26	0.19	0.97					0.83
P-O-I	-0.23	-0.32	-0.19	0.91				0.89
P-R-I	0.15	0.28	0.34	-0.27	1.01			0.92
F-P	0.24	0.20	0.16	0.27	0.33	0.94		0.86
C-M-A	0.3	-0.31	-0.24	0.34	0.39	0.32	0.92	0.82

The heterotrait monotrait (HTMT) correlation proportion analysis has been conducted to complement the Fornell and Larcker criteria. The projected values indicate that all the concepts have values below the maximum criterion of 0.85, which verifies the discriminant reliability of the constructions. The findings are discussed in Table 3.

Table 3: HTMT Verification Testing Result Analysis

Model	A-B-A	DDC	F-E-S	P-O-I	P-R-I	F-P	C-M-A
A-B-A							
DDC	0.37						
F-E-S	0.43	0.4					
P-O-I	0.43	0.51	0.59				
P-R-I	0.56	0.34	0.27	0.37			
F-P	0.25	0.29	0.43	0.59	0.45		
C-M-A	0.35	0.37	0.39	0.47	0.3	0.43	

Hypothesis Analysis

Within the framework of the PLS-SEM methodology, every hypothesis has undergone testing by boot-strapping, which included 6000 resamples and 456 instances. Testing for hypotheses is a valuable method for circumventing the need for parametric evaluations. A missing distance of five has been applied to the exogenous variables to achieve cross-validated redundant operation. The Stone-Geisser result was 0.68, indicating that the model has a satisfactory level of predictive significance. Using this procedure, it estimates the links' trajectory values, p-scores, and factors of determination (R2).

Moderator Analysis

The impact of the facilitators, Data Driven Concept (D-D-C), and LS was examined using multifunctional assessment. The effect of facilitator DDC was assessed by categorizing the respondent into two groups: Powerful DDC and Poor DDC. The impacts of LS as a facilitator are further classified into two groups: Strong LS and Weak LS. To assess the variations in p-values between the two subcategories of every facilitator, the bias-correlating boot-strapping method was used with 5000 resamples. The importance of the medium impact is acknowledged when the p-score discrepancy among the multiple groups for every facilitator is either below 0.06 or over 0.98 (i.e., a 5% margin of error).

The findings indicate that the regulating impacts of both facilitators are statistically significant. The findings are discussed in Table 4.

Table 4: Test Moderating Results

Pathways	Facilitators	p score variation	Status
F-E-S – D-D-C – P-R-I	D-D-C	0.95	Good
F-E-S – D-D-C – P-O-I	D-D-C	0.97	Good
P-O-I – L-S – F-P	L-S	0.04	Good
P-R-I – L-S – F-P	L-S	0.03	Good

Mediation Analysis

The research used the indirect effect verification technique to investigate the function of the factor as a mediator among the control factors and competitive Advantage. This included employing the bias-correlated expedited bootstrapping method with 6000 resamples. The outcomes are represented in Table 5.

Table 5: Control Variable Outcomes

Paths	Indirect effect	p value	Lower trust level	Upper trust level
Company size – O-P – C-M-A	0.13	0.03	0.05	0.18
Firm age – O-P – C-M-A	0.17	0.06	0.02	0.17
Industry category – O-P – C-M-A	0.19	0.08	0.07	0.11

The findings indicate that FP plays a valuable function as a facilitator. The findings also suggest that the credibility period in the bias-based bootstrapping spanning O-P is not equal to zero. The ranges for company size, firm age, and business type correspondingly 0.03–0.81, 0.04–0.25, and 0.04–0.18. This demonstrates that the variable is crucial in mediating the relationship between the control factors and C-M-A.

After verification, the approach is shown in Figure 2, considering all the given inputs.

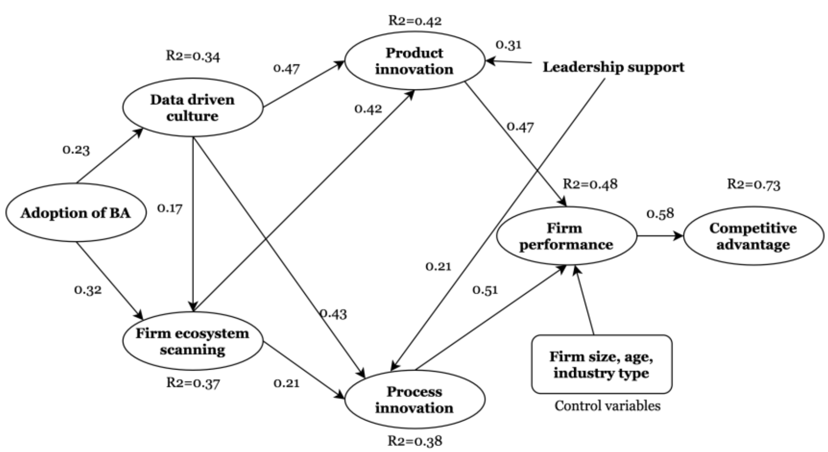

Figure 2: Validating Model

Common Method for Biasing

This research was done using information that the participants themselves provided. Therefore, conducting a Common Method Bias (CMB) analysis is essential. The questionnaire was used to validate the model through a PLS-SEM evaluation. The survey participants were guaranteed to keep their answers anonymous to minimize any potential bias in the replies. A post hoc Harman's Single Factor Testing (SFT) was undertaken to confirm the validity of CMB. The first component accounted for just 41.4% of the variation. It falls below the maximum threshold of 50%. The indicator variable approach has validated Harman's SFT. The study revealed that the disparity between CMB and adjusted CMB was consistently below 0.06 for all concepts, supporting Harman's SFT. CMB did not cause any distortion in the findings, ensuring that the information remains unbiased.

Results

The investigation generated 12 possibilities. Following statistical verification, it is evident that every hypothesis is confirmed. The study's findings on the impacts of A-B-A on D-D-C and F-E-S indicate that A-B-A has a more significant impact on F-E-S. This is supported by a correlation coefficient of 0.32, statistically significant at $p < 0.01$. The effect of D-D-C on F-E-S, specifically on the F-E-S – P-R-I connection and the F-E-S – P-O-I connection, suggests that the reducing impact of D-D-C on H6 (F-E-S – P-O-I) is at its strongest. This is evident from the path factor, which is 0.45 and statistically significant at a threshold of $^*p < 0.05$. The impact of F-E-S on P-O-I (H6) seems more robust than that of FES on PRI, as shown by the higher pathway factor of 0.42, which is significant at a level of $^{***}p < 0.001$. Comparing the impacts of P-O-I and P-R-I on F-P, it is evident that the influence of P-R-I on F-P (H9) is more substantial. This is supported by a path coefficient of 0.54, statistically significant at a significance score of $^{***}p < 0.002$. The impact of F-P on C-M-A (H10) is substantial, as shown by a path parameter of 0.57 and a significance score of $^{***}p < 0.001$. Regarding the moderating impact of LS on the links between P-O-I and F-P (H8) and P-R-I and F-P (H9), the influence of L-S on P-O-I-F-P (H8) is more substantial. This is shown by a path factor of 0.35, which is significant at a threshold of $p < 0.01$.

Regarding the coefficients of determination, the findings indicate that A-B-A accounts for 32% of the variability in D-D-C. A-B-A and D-D-C can account for 34% of the variability in F-E-S. The F-E-S model can account for 47% of the variance in P-O-I and 37% of the variance that exists in P-R-I. When considering P-O-I and P-R-I together, the F-E-S model will clarify 49% of the variability in F-P. F-P can elucidate C-M-A up to a 71% degree. The explanatory capacity of the framework is 75%.

5 Conclusion and Discussion

This research is the first to establish a connection between BA and the effective execution of processes and product invention, specifically enhancing an organization's ability to scan and gather information. The research is ground breaking in clarifying how the relationship between BA and creativity effectively function inside a DDC and how they eventually result in improved organizational performance. Based on practical facts, BA provides superior results when valuable data and logical methods are provided. Company analytics can enhance the outcomes of businesses by improving procedure efficiency and fostering good development, eventually increasing company value. Companies' absorptive ability significantly affects the impact of BA on productivity. The research has shown that to fully use the power of business analytics for creativity, firms should prioritize renewing the implications of a DDC and enhancing their capabilities. A DDC enables a company to update effectively to the ever-changing business conditions.

The research urges the BA group to acknowledge the significance of enhancing creativity to maximize corporate worth. Future scholars cultivate these ideas. The outcomes were derived from examining feedback from both big and medium-sized company workers. Small enterprises were excluded. This outcome needs to be comprehensively represented. Future studies address this issue to enhance the model.

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