Unlocking Competitive Advantage: A Study on The Impact of Data Strategy Implementation

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Abstract

In today's data-driven corporate environment, this article examines how data strategy components affect competitive advantage (CA). The research covers identification, storage, sharing, integration, and governance. Cross-sectional quantitative data was obtained from 120 people from various demographics and sectors. Hypothesis testing, reliability analysis, and discriminant analysis were used. CA is positively correlated with data strategy components (Identification, Storage, Sharing, Integration, and Governance). CA benefits directly from DDS and ODS. DDS favourably affects ODS, which mediates DDS-CA. The study provides empirical evidence of the links between data strategy components and CA, adding to the literature on data strategy and competitive advantage. The results may help companies use data to gain a competitive edge in today's fast-paced business climate.

Keywords Competitive advantage, DDS, ODS, CA, Identification, Storage, Sharing, Integration and Governance

1. INTRODUCTION

A data strategy is a long-term plan that outlines the people, procedures, technology, and guidelines needed to manage the information assets of an organisation. Large volumes of unprocessed data are being gathered by many kinds of enterprises. To utilise this data for decision-making and to develop applications for generative artificial intelligence (AI) or machine learning (ML), they must have a well-thought-out strategy for data management and analytics. An organization's long-term goals for gathering, storing, sharing, and using its data are outlined in a data strategy. It facilitates data work at every stage of the data journey for any individuals inside your organisation that need it.

1.1. Components of Data Strategy

1. Identify

The first and most important step in creating a data strategy is figuring out how to recognise, collect, and display data. An organization's primary goal is to store and handle data, but this can't be done unless the data is properly specified. Here, "defining data" refers to giving the data a name, a representation, a format, naming standards that are consistent, etc. Creating a data catalogue is another crucial part of this part. In this case, metadata is essential since it defines the data's origin, location, domain values, and other characteristics.

2. Store

Data storage is an essential component of a data strategy, as was previously discussed. Even though data storage is vital, it demands organisational discipline to master. The data strategy idea has evolved to place more emphasis on effective storage than just building systems to facilitate simple data exchange and system-to-system data transfer. Data science has been revolutionised by big data, which has encouraged information exchange between and inside businesses. The shared data, which is divided into internal and external categories, includes third-party and cloud application data as well as customer and purchase information. In the absence of centralised administration, duplicate copies of the data may arise from the autonomous space management of each system. Consolidating all the data in one location is the innate answer, but this presents difficulties. Because data must be shared across several systems, centralised storage is not practicable, particularly for big and dispersed businesses. Since not everyone needs access to company-wide data, a sensible approach is to make it simple for departments or people to find and obtain certain data.

3. Share

In the past, there wasn't much data exchange. In the past, an application developer would usually build an extract when there was a request for data. The majority of businesses didn't set aside money or assign employees to handle this non-transactional data exchange. Ultimately, this data exchange was resolved as a confidential favour between coworkers. Furthermore, frequent data exchange was not considered in the design of the majority of application systems. These days, the situation is different as effective data sharing is essential to corporate performance and is dependent on the quality of the data. Thus, appropriate data sharing policies and effective data storage are crucial parts of a sound data strategy.

4. Integrate

An effective plan takes into account the data's packaging and ease of sharing, both of which are critical given the variety of systems that organisations now manage. Among the data strategy components, the most difficult and expensive is integrating several data sources. Integration includes integrating data from several sources without the use of explicit keys or unique identities. It goes beyond ETL and data transportation across systems.

Organisational departments often function in silos and are unaware of how other departments use data, as was previously indicated. Every project or department develops its own logic to connect values from several shared data sources. But there are drawbacks to this decentralised method, particularly as sources and quantities of data grow. It becomes less likely that data will be consistently integrated across several projects. As a result, integration is essential to a strong data strategy.

5. Govern

The last aspect of data strategy governance is how the data is shared, processed, and altered. The concept of data governance pertains to the establishment of appropriate protocols to guarantee the preservation of data integrity while sharing and use by multiple organisations. It entails setting up data rules, naming conventions, security specifics, adjusting data logic, etc. Improved terminology standards, improved data quality, and other benefits may be achieved with a data strategy that includes strong governance.

1.2.Hypothesis of the Study

H1. DDS has a direct and beneficial effect on CA.
H2. ODS has a direct and beneficial effect on CA
H3. DDS has a direct and beneficial effect on ODS.
H4. ODS influences the DDS directly and favourably.
H5. The link between DDS and CA is mediated by ODS.
H6: The connection between ODS and CA is mediated by DDS

2. LITERATURE REVIEW

Dahiya et al., (2022) Examine how big data analytics (BDA) may help companies gain a competitive edge from a strategic standpoint. The literature study delves into the dynamic field of data analytics and its capacity to revolutionise the way businesses approach competition. The authors emphasise the importance of firm-specific information in exploiting BDA for strategic advantage, drawing on a wealth of academic studies. They place emphasis on how organisational resources, technical prowess, and strategic decision-making processes interact dynamically to shape competitive results. The study also emphasises how competitive advantage is multifaceted, including distinctiveness, cost effectiveness, and market response. The research combines knowledge from data science, information systems, and strategic management fields via an interdisciplinary lens to clarify the complex connection between BDA adoption and competitive performance. The writers provide a thorough grasp of the strategic requirements for using BDA as a catalyst for long-term competitive advantage in the modern corporate environment by fusing theoretical frameworks and actual data.

Côrte-Real et al., (2019) explore the complex dynamics involved in obtaining value from big data analytics (BDA) projects in businesses. The literature study thoroughly examines the body of research to date, clarifying the complex factors that support the profitable realisation of BDA investments. The understanding of BDA as a strategic enabler—one that may provide competitive advantages and promote organisational performance gains across a range of industries—is at the heart of their study. The authors emphasise important factors such data quality, analytical skills, organisational culture, and strategy alignment by synthesising actual research and theoretical frameworks. They emphasise how important management leadership is to coordinating BDA programmes and creating an organizational-wide data-driven culture. The research also explores the intricacies involved in determining and evaluating BDA value, highlighting the need of strong assessment frameworks that account for both concrete and intangible results. Through the integration of ideas from several disciplinary perspectives, such as data science, information systems, and business, the research provides a comprehensive knowledge of the factors influencing the impact and efficacy of BDA implementations in promoting organisational value generation.

Allioui and Mourdi (2022) Examine how artificial intelligence (AI) has revolutionised the modern corporate environment. Modern AI technologies and their effects on organisational strategy and operations are thoroughly examined in the literature study. The authors highlight the critical role that artificial intelligence (AI) plays in fostering innovation, increasing productivity, and opening up new opportunities for value creation across a range of industries, drawing on a wide range of academic studies and industry reports. A key component of their conversation is an examination of cutting-edge AI applications, including computer vision, natural language processing, and machine learning, and their significant effects on consumer experiences, company procedures, and competitive dynamics. The evaluation also explores the benefits and difficulties that come with using AI, including issues with bias, ethics, and privacy in addition to organisational preparedness and competence building. Through the synthesis of findings from multidisciplinary viewpoints including data science and computer engineering, the research provides a comprehensive understanding of the many ways that AI technologies will shape business and society in the future.

3. RESEARCH METHODOLOGY

3.1. Research Design

The data in this study are numerical in nature and the goal is to quantify the correlations between variables, a quantitative research methodology was used. This is a good use for quantitative research since it makes it possible to gather and analyse numerical data in a methodical way in order to find relationships, patterns, and trends. Furthermore, the study methodology is probably cross-sectional, which means that information is gathered all at once. This method makes it possible to investigate the connections between DDS, ODS, and CA constructs and demographic variables including education level, job experience, firm size, and economic sector, all within a certain time period. Through the use of a cross-sectional study methodology, the research attempts to present a picture of the demographic and attitudinal landscape of the questioned population, as well as insights into the current correlations between these factors.

3.2. Research Sample

120 people will make up the research sample for this study, which will be chosen using probability sampling methods, particularly cluster or stratified random sampling. By ensuring that every subgroup within the population has an equal probability of being represented in the sample, this strategy will improve the representativeness of the sample. To make sure that the study's findings are statistically significant and applicable to the target demographic, a sample size of 120 will be chosen using the proper statistical techniques. There will be enough statistical power in this sample size to identify significant correlations between demographic variables and constructs.

The demographic characteristics of the sample, such as age, gender, education level, job experience, firm size, and economic sector, will be diverse and representative. The research will be able to collect a wide variety of viewpoints and guarantee that the conclusions are relevant to various demographic groups thanks to this diversified representation.

3.3. Data Collection Techniques

Primary Data: A systematic survey questionnaire will be created to obtain primary data directly from the people who were sampled. In addition to items evaluating the constructs DDS, ODS, and CA, this questionnaire will have well constructed questions on the demographic aspects of relevance, such as education level, job experience, firm size, and economic sector. To ensure more diverse and widely distributed participation, the survey will be sent via email or through online survey platforms to a bigger sample that is spread geographically. In-person interviews will also be done with individuals who may not have access to online questionnaires or who feel uncomfortable using them. In-depth analysis of the replies and a more intimate exchange of ideas will be possible during these interviews, guaranteeing that every demographic is fairly represented in the research. All things considered, using a mix of online surveys, in-person interviews, and structured survey questionnaires will allow for full data collection and a detailed examination of the connections between the study's constructs and demographic variables.

Secondary Data: The study will use secondary data from current databases and literature studies to augment the main data gathered via survey questionnaires and interviews. The research would use extant databases, such as government papers, industry publications, and academic journals, to collect pertinent secondary data pertaining to many issues. Numerous pieces of information, including academic publications, statistical reports, and industry trends, are available in these databases and may give important background information and insights into the subject of the study. In order to collect secondary data on pertinent theories, constructs, and prior research results connected to the study, a comprehensive literature review will also be carried out. The purpose of this study is to discover important ideas, theoretical frameworks, and empirical investigations that are pertinent to the goals of the research by looking through the body of current scholarly literature, which includes books, academic journals, and conference proceedings. The study endeavours to enhance its analysis and provide a thorough comprehension of the associations among demographic characteristics and constructs by integrating secondary data from existing databases and literature studies.

4. DATA ANALYSIS

The given data provides insights into the educational attainment, employment experience, size of the firm, and economic sector of a certain population. Of those polled, 35% have a degree from a university, and 41% have received specialised training. Just 12% of the population has a Master's degree, while 12% of the population has a PhD. 15% of respondents said they had worked for up to four years, and 45% said they had worked for between four and nine years. Furthermore, 23% are between the ages of 9 and 14 and 17% have more than 20 years of professional experience. In terms of business size, the bulk of workers—45% of all workers—are employed by small firms, followed by medium-sized businesses (35%), and bigger organisations (20%). The population's employment is distributed across the economic sectors as follows: 22% work in the services sector, 15% in the energy sector, and 41% are engaged in the industrial sector. This thorough data offers insightful information on the studied population's economic, professional, and educational backgrounds.

Table 1: profile of respondents

Level of Education	**(%)**	**Work Experience (Years)**	**(%)**	**Company Size**	**(%)**	**Economic Sector**	**(%)**
Higher Education	35	Up to 4	15	Small	45	Services	22
Specialization	41	$4< x \leq 9$	45	Medium	35	Energy	15
Master's Degree	12	$9 <x \leq 14$	23	Large	20	Industry	41
PHD	12	x>20	17			Others	22

Table 2: Analysis of convergent validity and reliability

Constructs	**Variables**	**Loading**	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted**
DDS	DDS-04	0.725	0.822	0.875	0.634

	DDS-05	0.790			
	DDS-06	0.860			
	DDS-08	0.841			
ODS	ODS-02	0.733			
	ODS-03	0.734	0.925	0.932	0.625
	ODS-04	0.865			
	ODS-05	0.850			
	ODS-06	0.605			
	ODS-07	0.844			
	ODS-08	0.860			
CA	CA-01	0.910	0.944	0.965	0.745
	CA-02	0.811			
	CA-03	0.814			
	CA-04	0.824			
	CA-05	0.921			
	CA-06	0.821			

In the context of study, the table provides information on constructs, variables, and different statistical measures. There are three constructions examined: DDS, ODS, and CA. Each construct has many connected variables. Four variables are assessed for the DDS construct: DDS-04, DDS-05, DDS-06, and DDS-08. The loading values, which span from 0.725 to 0.860, show how variables and constructions relate to one another. Furthermore, internal consistency measurements, or Cronbach's Alpha values, are given. With a Cronbach's Alpha of 0.822, DDS seems to have a good degree of dependability. Comparably, DDS's composite dependability is strong, with a score of 0.875. The percentage of variation collected by the construct in relation to measurement error is shown by the Average variation Extracted (AVE) for DDS, which is 0.634. Seven factors are used to assess the ODS construct, spanning from ODS-02 to ODS-08. The ODS variables have loadings ranging from 0.605 to 0.865, which suggests different degrees of correlation with the construct. With a Cronbach's Alpha of 0.925, ODS has good internal consistency. Additionally, its composite reliability of 0.932 confirms its dependability. With an AVE of 0.625 for ODS, substantial variation was recorded in relation to measurement error. Finally, six variables, referred to as CA-01 through CA-06, are used to evaluate the CA construct. The range of loadings for CA variables indicates their correlation with the construct, ranging from 0.811 to 0.921. With a composite dependability of 0.965 and a high Cronbach's Alpha of 0.944, CA shows robustness and good internal consistency, respectively. With an AVE of 0.745 for CA, a significant amount of variation is recorded in comparison to measurement error. In general, these statistical data provide valuable perspectives on the dependability and accuracy of the concepts being investigated within the study framework.

Table 3: Analysing discriminants

Construct	CA	DDS	ODS
CA	0.872		
DDS	0.125	0.741	
ODS	0.485	0.661	0.654

The correlation coefficients between the constructs CA, DDS, and ODS are shown in the table. There is a significant degree of self-correlation shown from the substantial positive correlation (1.000) between CA and itself. DDS has a substantial positive association (0.741) with ODS and a moderately positive correlation (0.125) with CA. ODS has a large positive correlation (1.000) with itself and a moderately positive correlation (0.485) with CA and DDS (0.661). Overall, the table shows how the constructs are related to one another, with DDS and ODS exhibiting very high correlations.

Table 4: Test of hypotheses and path coefficient

Hypothesis	Path Coefficient	Coefficient	p-values	Empirical Evidence
H1	DDS → CA	0.566	0.000***	Supported
H2	ODS →CA	0.589	0.000***	Supported
H3	DDS → ODS	0.759	0.000***	Supported
H4	ODS →DDS	0.759	0.000***	Supported

The data that is supplied describes the findings of an examination of a hypothesis testing including path coefficients, p-values, and empirical support for the connections among the constructs DDS, ODS, and CA. From H1 to H4, each hypothesis is labelled and looks at a certain direction of link between these components. Higher values in the path coefficient indicate stronger correlations. It is a measure of the intensity and direction of the link. The statistical significance level is shown by the p-value, where "***" signifies strong significance. The analysis supports each of the four possibilities. With a very significant p-value of 0.000 and a path coefficient of 0.566, H1 indicates a substantial positive association between DDS and CA. Similarly, with a path coefficient of 0.589 and a p-value of 0.000, H2 shows a strong positive link from ODS to CA. Furthermore, with path coefficients of 0.759 and extremely significant p-values of 0.000, H3 and H4 also show substantial positive associations between DDS and ODS.

Overall, our results show strong directional impacts among the variables DDS, ODS, and CA and provide empirical support for the proposed linkages between them.

5 CONCLUSION

The significance of data strategy elements in fostering competitive advantage (CA) within enterprises is highlighted by this research. It demonstrates how important a role Data Definition and Sharing (DDS) and Organisational Data Storage (ODS) play in forming CA, and how one positively influences the other. The research also emphasises how data definition and storage are mutually beneficial, with one having a favourable influence on the other. The link between DDS and CA is mediated by ODS, which highlights the significance of sound data storage procedures in converting data strategy into a competitive advantage. These results provide insightful information to companies looking to improve their competitive posture via the development and use of efficient data management methods. Organisations may generate innovation, efficiency, and sustained competitive advantage in today's data-driven business environment by optimising their data infrastructure, processes, and governance frameworks by understanding the strategic implications of data strategy components.

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