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Evolution of Big Data Analytics and Its Business Applications

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Abstract
The Evolution of Big Data Analytics and its Business Applications" is an academic study that explores the development and current significance of Big Data Analytics (BDA) in running a company. The research investigates the impact of BDA on businesses and addresses its challenges. By examining the evolution of this field, we aim to add to the existing knowledge and enable organizations to leverage the transformative potential of BDA, thereby staying competitive in this data-driven era. Based on the analysis, we provide recommendations for companies and suggest conducting a deeper and more extensive study on the role of BDA in various industries and sectors.

***Keywords*:** Big Data Analytics, Information Technology, Data Quality, Data Management, Business Application, Future trends.

Introduction

As we set sail into the vast sea of new frontiers in business, academia, and life itself, we find that our lives and various aspects of society, business, government, and healthcare are touched by the digital. A digital footprint now follows almost everyone in the world. The winds of change blow fast and transform how we live, work, interact, communicate, and go about our lives. A gentle whisper in the morning sunrise urges us to embrace the digital revolution that disrupts everything around us like a storm in the ocean. This storm is here to stay, and its aftermath may bring a different world. However, one thing is certain; this storm has given birth to a new powerhouse, whose importance is felt by every person, company, government, and society, and that is data. Data, they say, is valuable, like oil was in the past century. Data needs to be processed like a good recipe, with various ingredients. In the case of data, the ingredients are high volume, high velocity, variety, and various values. The process involves normalization of the variety of data and finally converting the data into information through the process of Analytics. This process gives birth to a new species in the evolutionary cycle of technology, called big data analytics. In the rapidly evolving landscape of contemporary business operations, data has emerged as the lifeblood of decision-making, strategy formulation, and competitive advantage. The digital age has ushered in an era where organizations of all sizes are inundated with vast volumes of data. This data deluge, often referred to as the Big Data phenomenon, has transformed the way businesses operate, creating opportunities and challenges in equal measure. At the heart of this transformative wave lies Big Data Analytics (BDA), a field that has revolutionized how organizations harness and derive value from their data resources (Davalos, 2017).

Big Data Analytics (BDA) refers to the use of advanced technologies and techniques to analyze large and complex datasets. By analyzing such data, businesses can uncover patterns, trends, and insights that were previously hidden. This enables businesses to make data-driven decisions, identify new market opportunities, optimize processes, and enhance customer experiences. As technology continues to advance and data becomes increasingly available, BDA is expected to play an even more crucial role in shaping the future of business operations (G. Thippanna et al., 2023; (Dominici, 2022)

The world of business has undergone a significant transformation thanks to big data analytics. It has revolutionized the way organizations operate by providing valuable insights that aid in making informed decisions. The impact of big data analytics on business operations has been remarkable, leading to improved decision-making and increased efficiency(Faridoon et al., 2024).

In today's world, we are generating an enormous amount of data at an unprecedented speed, volume, variety, and value. Big Data comes from various sources, including Information Technology, the Internet of Things, social media, applications, and websites. This data is immensely useful for businesses as it provides insights into customer behavior, market trends, and other crucial aspects of the industry.(Aitchison, 2024).

Big data analytics has resulted in major improvements in Artificial Intelligence (AI), Machine Learning, and Natural Language Processing (NLP). These technologies help businesses to analyze and comprehend vast quantities of data more efficiently. For example, AI algorithms can analyze large datasets and detect patterns to make predictions. Similarly, NLP can assist businesses in understanding customer sentiment by analyzing their interactions on social media platforms(Aattouri et al., 2023)

The influence of big data analytics on businesses is significant and cannot be underestimated. With the assistance of advanced technologies such as AI, Machine Learning, and NLP, organizations can now make informed decisions based on data, enhance their efficiency, and gain a competitive edge in the market(Schmitt, 2023).

Significance of the Research

The research conducted aims to highlight the importance of big data analytics (BDA) for organizations looking to enhance their efficiency, innovation, and competitiveness. BDA has revolutionized the decision-making process for companies, enabling them to make more informed decisions and gain a competitive edge in their respective industries. By identifying patterns and trends in large datasets, companies can make accurate predictions and better strategic plans. The study also examines the consistency of perception towards BDA across various sectors to identify its potential benefits. Additionally, it explores whether the size of an organization affects its adoption and utilization of BDA.

Problem Statement

In the current rapidly evolving business landscape, companies need to leverage Big Data Analytics (BDA) in order to stay ahead in the competition. However, this can be a challenging and risky undertaking. In order to fully harness the potential of BDA, it is important to comprehend its relationship with information science, technology, and business practices. This comprehension can aid organizations in optimizing BDA's transformative potential. This research aims to shed light on the aforementioned problem statement.

Research Question

The following statement outlines the primary research question that this study aims to answer: How has the evolution of big data analytics influenced business practices, and what are the implications for organizations in the data-driven era? This study intends to explore the potential advantages and disadvantages of implementing big data analytics in organizations, and to determine its overall impact on business practices. Additionally, this study will investigate whether there is a significant difference in the perception of future trends of big data analytics across industries. Moreover, it will examine whether the size of the organization affects the adoption and utilization of big data analytics.

Purpose and Contribution

The main goal of this capstone project is to conduct a detailed investigation into the evolution of Big Data Analytics and its applications in the business world. By achieving the research objectives defined earlier, this study aims to contribute to the existing knowledge by providing a comprehensive understanding of BDA's evolution and its profound impact on businesses. Such an understanding can enable organizations to make well-informed decisions, formulate effective strategies, and leverage the transformational potential of Big Data Analytics to their advantage.

Research Design

The research design for this capstone project involves a multi-faceted approach, combining historical analysis, technological examination, empirical assessments, and future trend analysis. It incorporates a review of scholarly literature, case studies, and empirical data analysis to provide a comprehensive perspective on the evolution of BDA and its implications for businesses.

Literature Review

Background

In order to understand the full extent and importance of this study, it is crucial to explore the background literature and key concepts related to information technology, information science, and information systems. This includes examining how these fields have evolved over time and their current state, as well as their potential future developments(Greyson, 2016).

Furthermore, it is essential to understand the impact that these fields have had on business practices, especially in relation to Big Data Analytics. This includes exploring the various technologies and tools employed in this domain, such as data mining, machine learning, and predictive analytics, and how they have revolutionized the way organizations handle data.(Kumar & Singh, 2019)

By gaining a deeper understanding of these concepts, we can appreciate their significance in the wider context of technological innovation and advancement.(Ng, 2018) This will help us to better comprehend how businesses can leverage these tools and techniques to obtain a differentiation with reference to their competoitor, optimize their operations, and ultimately drive growth and success.(Shah, 2022)

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The Definition of Information

In the context of business, understanding the significance of data and analytics is crucial and hence it's important to delve deeper into the multifaceted concept of information. Information comprises a wide variety of components, including raw data, knowledge, and insights, all of which are crucial in driving the decision-making process.(Dasgupta, 2017) Raw data refers to the unprocessed information collected from various sources, such as customer feedback, market trends, and financial reports. Knowledge, on the other hand, involves the application of expertise and experience to analyze and interpret data effectively. This can be achieved through specialized training or by collaborating with other professionals in the field.(Zurada & Karwowski, 2011)

Insights are the most valuable part of information and can be obtained by analyzing raw data and knowledge. These insights help businesses to gain a competitive advantage by providing them with the necessary information to make informed decisions. To create useful insights, businesses must use advanced analytics techniques such as predictive modeling, data visualization, and machine learning. By doing so, they can identify patterns, trends, and correlations in their data, which can be used to identify opportunities and mitigate risks("Leveraging Business Data Analytics Using Machine Learning Techniques," 2023).

In summary, the concept of information encompasses a diverse range of components that are critical in driving business success. By understanding the nuances of each component and utilizing advanced analytics techniques to generate insights, businesses have the ability to make well-informed decisions that can drive their growth and profitability (Millerman, 2023)

The Origins of Information Science

Information Science is a multidisciplinary field that involves the study of various aspects of information, including its creation, organization, dissemination, and utilization. It encompasses a range of topics related to information management, such as data analysis, database design, information architecture, and information retrieval. Information Science also intersects with other disciplines, such as computer science, library science, and communication.(Meadow, 1994)

The field of Information Science has evolved over time, driven by advances in technology, changes in business practices, and shifts in societal norms. As new information technologies emerge, Information Science seeks to understand how these technologies can be used to improve the way we create, organize, and access information. At the same time, it also grapples with the ethical and societal implications of these technologies, such as issues of privacy and security.(Arunachalam, 2002)

Overall, Information Science is a critical field that underpins many aspects of modern society. It plays a crucial role in helping individuals, organizations, and societies make sense of the abundance of information that surrounds us, and in developing the tools and techniques needed to manage this information effectively.(Williamson & Roberts, 2010)

Information Science, Information Technology, Information Systems (MIS), and Business

The fields of Information Science, Information Technology, and Information Systems (MIS) are interconnected and essential for the effective management and utilization of information in modern business settings.(English, 1996)

Information Science is a field of study that deals with the effective management of information. It covers both theoretical and practical aspects, including the processing, storage, and retrieval of information. The main areas of focus in Information Science are information architecture, knowledge management, and information retrieval. Professionals in this field aim to create systems that are user-friendly and efficient by understanding how information is organized and accessed (Frické, 1998).

Information Technology is the practical application of computing resources to process and manage data. It comprises the use of hardware, software, and network technologies to develop and support information systems. This field is continuously evolving with the emergence of new technologies and tools that help businesses manage and analyze data more efficiently(Cohn, 2017).

Information Systems (MIS) is a broader field that encompasses both Information Science and Information Technology. It focuses on the design, implementation, and management of information systems that support business operations and decision-making processes. MIS professionals work to ensure that information systems are efficient, secure, and aligned with business goals. They must also stay up-to-date with the latest technologies and trends in order to provide the best possible solutions to businesses.(Robey & Taggart, 1982)

To effectively manage and utilize information, businesses must focus on certain critical fields. These fields work together to improve efficiency, increase productivity, and drive success. By seeking the knowledge and expertise of information professionals, businesses can gain a competitive edge in today's fast-paced digital world (Hermans, 1996).

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The Differences between Information Technology and Information Systems

Information Technology (IT) is the utilization of technology to manage information and data. It includes software development, network infrastructure, and cybersecurity. IT is a crucial component of modern business operations as it allows companies to efficiently and securely store, process, and transmit data (Hodgson & Dunne, 1990)

Information Systems (IS), on the other hand, is a branch of IT that focuses on how technology can be used to support business processes. IS includes the people, processes, and technology that work together to create, process, and distribute information within an organization. This includes everything from basic email and file-sharing systems to complex enterprise-level software applications.(Haake & Wang, 1999)

The primary focus of IT is on the hardware and software that make up the technology infrastructure. It involves designing, implementing, and managing the systems that enable businesses to operate efficiently. IS, on the other hand, is concerned with how these systems can be used to support specific business processes. This involves analyzing business requirements, designing information systems that meet those requirements, and managing the implementation and ongoing operation of those systems.(Silver, 2014)

In summary, IT is the foundation on which information systems are built. It provides the hardware and software infrastructure that enables businesses to manage their data effectively. IS is the application of that infrastructure to specific business processes, enabling companies to use technology to streamline their operations and gain a competitive advantage in their respective sectors.(Martínez & Kuri, 2011)

Information Systems (MIS) and Information Science

Information Systems (MIS) are a crucial component of modern organizations, playing a pivotal role in the collection, processing, and dissemination of data. The primary objective of MIS is to provide decision-makers with timely and accurate information that can be used to make informed choices. MIS typically consists of hardware, software, and communication technologies that work together to manage data in an efficient and effective manner.(Robey & Taggart, 1982)

Information Science is a field that studies the theoretical foundations and practical applications of information systems. It focuses on how information is created, stored, processed, and accessed. Information Science is an interdisciplinary field that draws upon computer science, library science, cognitive psychology, and other related fields.(Frické, 1998)

The design and implementation of MIS rely heavily on the principles of Information Science. Information Science provides a systematic and scientific approach to understanding how information is managed and used. By leveraging the principles of Information Science, businesses can develop and implement better MIS that meets their organizational needs.(Kendall & Kendall, 1981)

Overall, MIS and Information Science are intertwined, with Information Science providing the theoretical foundations and practices underpinning MIS. By using these principles, businesses can create efficient, reliable, and secure information systems that help them make informed decisions and gain a competitive edge in the market.(Parsons & Wand, 2008)

The Impact of Information Science on Business Practices Involving Big Data Phenomena and Big Data Analysis

In today's business landscape, the impact of BDA cannot be overstated. As businesses continue to accumulate vast amounts of data, there is a growing need for methods to extract insights from this data that can inform decision-making. This is where the field of Information Science comes in. Information Science provides a comprehensive theoretical framework and methodologies for managing, processing, and analyzing massive datasets to uncover valuable insights. With the help of sophisticated analytical tools and techniques, businesses can develop a thorough understanding of their operations and market dynamics, enabling them to identify trends, patterns, and opportunities that would have otherwise remained hidden. Businesses can gain a competitive edge by leveraging Information Science and Big Data Analytics to make informed decisions and optimize operations..(Tayeb, 2023)

The Evolution of Big Data

The current era has seen the emergence of Big Data, which has transformed the way we manage data. Essentially, Big Data refers to the vast amounts of data generated in various forms, such as structured data, unstructured data, and semi-structured data. The volume of data produced is enormous, and its velocity is unprecedented, with data being generated in real-time. Moreover, the variety of data types is vast and diverse, ranging from text, images, video, and audio to sensor data, social media posts, and customer feedback. The accuracy, completeness, and reliability of the data, which are critical attributes in data analysis, are referred to as the veracity of the data(Gong, 2013).

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The growth of Big Data has been influenced by significant advancements in technology, including machine learning, cloud computing, and data analytics. These technological breakthroughs have made it possible for organizations to extract valuable insights from their data, leading to improved decision-making, increased efficiency, and the development of new products and services. By using Big Data analytics, organizations can now identify patterns and trends in the data that were previously undetectable, which gives them a competitive edge in the market. The potential of Big Data to drive innovation and create new possibilities is limitless, and its transformative power is yet to be fully realized (Sabharwal & Miah, 2021)

Big data analytics has become a critical tool in the business world, allowing organizations to make informed decisions and gain valuable insights. By analyzing large volumes of data from various sources, businesses can identify patterns, trends, and correlations that may not be evident through traditional analysis methods. This can significantly improve their comprehension of customer behavior, market trends, and operational efficiency(Guo, 2019).

Data science and big data have become integral aspects of business strategy, with many senior executives recognizing their importance in sustaining and improving competitiveness. Incorporating data analytics into decision-making processes can provide organizations with a competitive advantage by driving growth, improving operational efficiencies, and supporting strategic planning.(Boncea et al., 2017)

The emergence of big data has brought about new challenges for businesses. With the abundance of data available, organizations must devise effective ways to manage and utilize this data to derive valuable insights. Moreover, incorporating big data analytics in industrial and business processes can improve organizational agility. (Sghaier, 2020). This transition towards big data analytics allows organizations to predict and address unpredictable issues, ultimately improving process performance.(Turi et al., 2023)

Big Data analytics, evolving rapidly (Chen et al., 2012), is transforming various business aspects. Its historical context lays important groundwork (Laney, 2001), connecting key milestones from mathematical statistics to recent techniques like Machine Learning (ML) and Artificial Intelligence (AI) (Wang et al., 2016). Research signifies its vital role in e-business, opening new business models (Bughin et al., 2010).

Benefits and Utilization of Big Data Analytics by Companies

Companies like Amazon and Netflix have leveraged Big Data for improved decision-making, efficiency, and customer experience (Brynjolfsson et al., 2011). However, the growth brings challenges – data security and privacy, lack of skilled personnel, and infrastructure issues (Kshetri, 2014). Future trends indicate a shift towards Predictive Analytics and greater AI integration (Chui et al., 2018).

Utilizing big data analytics has the significant advantage of making well-informed and precise predictions. Through analyzing vast datasets, organizations can apply advanced analytics techniques to identify patterns and trends that can help them predict future outcomes. This is particularly valuable in industries where forecasting market trends or customer behavior is critical to success (Dymora et al., 2022).

Moreover, the integration of big data analytics can also enhance decision-making processes within organizations. By analyzing data from various sources, such as customer feedback, sales data, and market trends, businesses can make more data-driven decisions that are based on objective insights rather than gut feelings or intuition. This can result in improved efficiency and effectiveness in decision-making, as data speaks better than experts. By relying on data-driven insights, organizations can minimize the risks associated with subjective decision-making and increase the likelihood of making informed choices that align with their strategic goals(Liu et al., 2021)

In addition, big data analytics can also contribute to the development and implementation of new business models. By analyzing large volumes of data, organizations can identify untapped market opportunities, understand customer preferences, and design innovative products and services tailored to meet those needs. This allows businesses to stay ahead of the competition and continuously adapt to changing market demands (Chatfield et al., 2018)

Furthermore, the application of big data analytics has the potential to improve cooperation between public and private sectors. By sharing and analyzing data, organizations can improve transparency and participation, leading to more effective collaborations and partnerships. This can be particularly beneficial in areas such as urban planning, public health, and environmental sustainability, where multiple stakeholders need to work together to address complex challenges Big data analytics has the potential to improve customer experiences in real-life situations. Analyzing customer data helps organizations gain insights into individual preferences, behaviors, and needs. This enables them to offer personalized and tailored experiences, ranging from customized recommendations for online shopping to personalized healthcare treatment plans. By leveraging big data analytics, organizations can improve customer satisfaction and loyalty(Arena & Pau, 2020)

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Bibliographic Analysis

Scopus journal data based was used to extract data and seventy eight Journal data was downloaded from Scopus database where paper related to evolution of big data Analytics was written.
Around ninety eight citations of reoccurrence of authors was found.

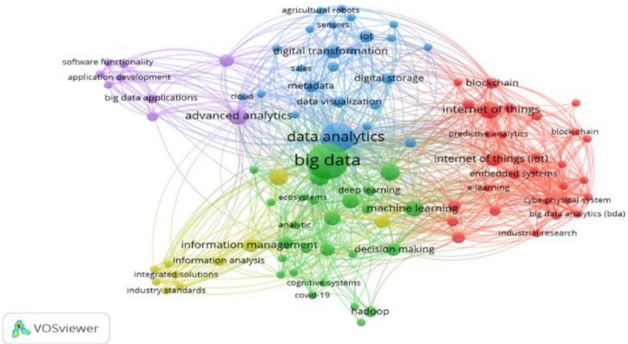

Figure 1 *Bibliographic Analysis Reoccurrence.*

The paper was predominately written on five topics: business intelligence, upstream oil industry operations, real-time operational intelligence, and unified framework.

Figure 2 *Bibliographic Analysis Key area of research papers.*

A total of nine authors were found on Scopus who have predominantly written on the topic of evolution of big data analytics.

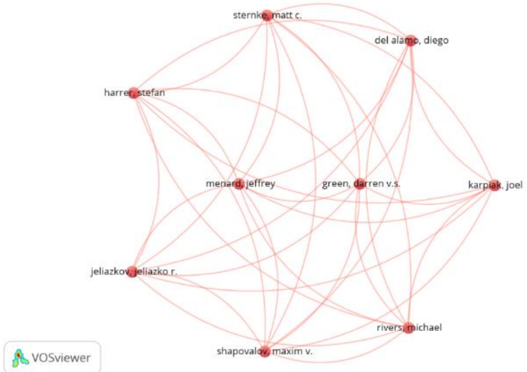

Figure 3 *Bibliographic Analysis Key Authors.*

Research Methodology

This chapter describes the research methodology for the capstone project, including research design, sampling technique, data collection, analysis, ethical considerations, limitations, and survey method.

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Scope of Research

This research aims to analyze the effects of big data analytics on decision-making processes in business organizations. It also examines the relationship between the use of big data analytics in business applications, organizational performance, and competitive advantage. Moreover, the study investigates the perceptions of future trends in big data analytics across industries, and how organizational size influences the adoption and utilization of big data analytics.

Research Problem

The primary research problem that this study addresses is to gain an in-depth understanding of the diverse impact that big data analytics has on business operations, decision-making processes, and the overall performance of an organization. Moreover, the research aims to identify factors that influence these impacts, such as emerging trends, technological advancements, successful applications, and organizational size.

Research Objectives

The primary objectives of the research are:

1. To assess the impact of big data analytics on the decision-making process in business organizations.
2. To explore the correlation between business applications of big data analytics and organizational performance.
3. To examine the perception of future trends in big data analytics across different industries.
4. To investigate the influence of organizational size on the adoption and utilization of big data analytics.

Research Methodology

Research Design

The research design adopted for this study is a mixed-methods approach. It combines quantitative analysis through statistical methods and qualitative insights gathered through surveys and interviews.

Sampling Technique

A purposive sampling technique was employed to select participants who have direct experience or expertise in the field of big data analytics within various industries. The sample size was determined to ensure adequate representation across different sectors.

Data Collection

Data was collected through surveys and interviews. The survey instrument included a questionnaire designed to gather quantitative data, while interviews provided qualitative insights. The surveys were distributed electronically, and interviews were conducted in-person and virtually.

Data Analysis

Quantitative data were analyzed using statistical tools such as SPSS. Descriptive statistics, correlation analyses, ANOVA, and regression analyses were performed to assess relationships between variables. Qualitative data from interviews were thematically analyzed to derive meaningful insights.

Ethical Considerations

Ethical guidelines were followed throughout the research process. All participants gave informed consent, and confidentiality and anonymity were maintained.

Limitations

The study acknowledges certain limitations, including the potential for response bias in surveys, variations in participant perspectives, and constraints related to the generalizability of findings.

Survey Method

The survey consisted of a structured questionnaire with both closed-ended and Likert scale questions. The questionnaire covered topics such as the impact of big data analytics, perceptions of future trends, and organizational practices.

Sampling Method - Sampling Process

The data collection process involved defining the population of interest, identifying the sample frame, specifying the sample unit, selecting participants, distributing a questionnaire, and analyzing the data.

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Hypothesis

- H1: The evolution of big data analytics has significantly impacted the decision-making process in business organizations.
- H2: Business applications of big data analytics are positively correlated with organizational performance and competitive advantage.
- H3: There is a significant difference in the perception of the future trends of big data analytics across industries.
- H4: Organizational size influences the adoption and utilization of big data analytics for business insights.

Data Analysis and Finding

The Data Analysis has been Done using Cronbach's Alpha for reliability Analysis, Regression, Anova and Pearson Test.

Cronbach's Alpha Reliability test:
Table 1Reliability Test

Case Processing Summary

		N	%
Cases	Valid	48	96.0
	Excluded[a]	2	4.0
	Total	51	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.636	13

The case processing summary indicates that there were 50 cases in total, with 48 cases considered valid and included in the analysis, while 2 cases were excluded due to listwise deletion based on all variables in the procedure.
The reliability statistics show a Cronbach's Alpha coefficient of .636, indicating moderate internal consistency among the 13 items included in the analysis.

Demographics Analysis

Age

The research sample size included fifty one participants of which 15.75% were in age group of 18-25, 25.5% of the participant were in the group of 26-35, 39.2% of the participants were in the age group of 36-45, while 15.7% of the participants were in the age group of 46-65 while a very small percentage was in age group of 56 and above.

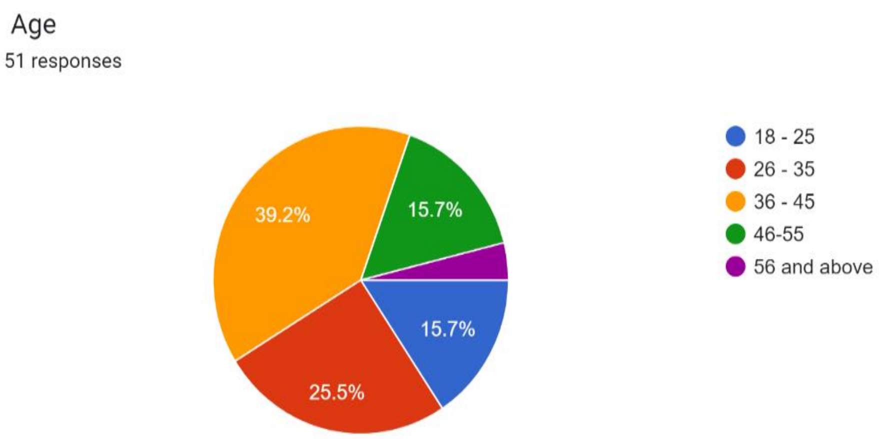

Figure 4 Age of Participants

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Gender

The gender of the participant in the survey 70.6% participants in survey were of male gender while 29.4% participants in the survey were female Gender.

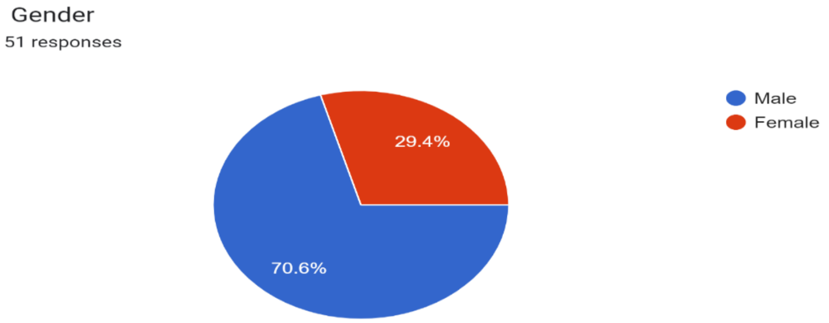

Figure 5Gender of Participants

Industry Experience

Amongst the participants who participated in the survey 20.5% were having 0-5 years' work experience, 13.7% had 6-10 years of work experience, 27.5% of the participants had 11-15 years of work experience, while 21.6% of the participants had 16-20 years of work experience, and 11.8% of the participants involved in survey question answering had over 20 years of work experience.

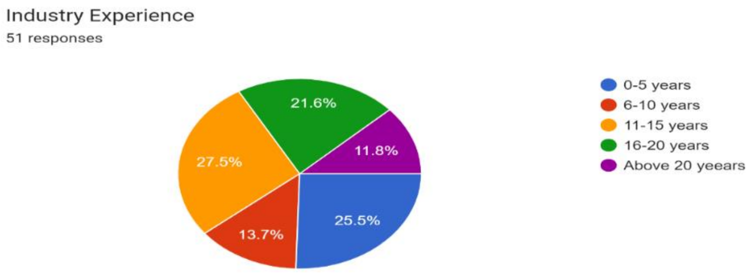

Figure 6 Industry experience of participants.

Hypothesis 1:

H0: The evolution of big data analytics has not significantly impacted the decision-making process in business organizations.

H1: The evolution of big data analytics has significant impacted the decision-making process in business organization.

We use Regression Analysis and Anona to check this hypothesis.

Regression

Table 2 Regression

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Big Data Analytics has significantly evolved over the past decade'ᵇ	.	Enter

a. Dependent Variable: Big Data Analytics has transformed business operation and decision-making processes. "

b. All requested variables entered.

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Table 3 Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.093[a]	.009	-.012	.713

a. Predictors: (Constant), Big Data Analytics has significantly evolved over the past decade.

Table 4 ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.210	1	.210	.414	.523[b]
	Residual	24.370	48	.508		
	Total	24.580	49			

a. Dependent Variable: Big Data Analytics has transformed business operation and decision-making processes. "

b. Predictors: (Constant), Big Data Analytics has significantly evolved over the past decade.

Table 5 Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.000	.356		11.228	<.001
	Big Data Analytics has significantly evolved over the past decade.	.239	.371	.093	.644	.523

a. Dependent Variable: Big Data Analytics has transformed business operation and decision-making processes. "

1. **Model Summary:**

The R-squared value is very low (R-squared = 0.009), suggesting that only a very small proportion of the variance in the decision-making process is explained by the evolution of big data analytics.

2. **ANOVA:**

The ANOVA table shows that the regression model is not statistically significant ($F = 0.414$, $p = 0.523 > 0.05$). This indicates that the relationship between the evolution of big data analytics and the decision-making process is not significant.

3. **Coefficients:**

The coefficient for the independent variable "Big Data Analytics has significantly evolved over the past decade" is not statistically significant ($t = 0.644$, $p = 0.523 > 0.05$). This suggests that there is no significant relationship between the evolution of big data analytics and the decision-making process.

In summary, based on the regression analysis results, we fail to reject the null hypothesis (H0). This means that the evolution of big data analytics does not significantly impact the decision-making process in business organizations, as hypothesized. The independent variable does not have a significant effect on the dependent variable.

Hypothesis 2:

H0: Business applications of big data analytics are not positively correlated with organizational performance and competitive advantage

H1: Business applications of big data analytics are positively correlated with organizational performance and competitive advantage.

We have used Bivariate Correlations for test the hypothesis.

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Table 6 Correlations

Correlations

		Big Data Analytics has significantly evolved over the past decade.	Our organization has evolved its data infrastructure to harness the potential of big data analytics. "	The evolution of big data analytics has transformed data management and analytics in our organisation "	Big Data Analytics has transformed business operation and decision-making processes. "	Big Data analytics has enhanced our understanding of customer preferences and behaviour. "	The use of big data analytics has improved our operational efficiency and resource allocation "	Successful business applications of big data analytics are prevalent in my industry or industries I am familiar with. "
Big Data Analytics has significantly evolved over the past decade.	Pearson Correlation	1	.384**	.446**	.232	.108	.456**	.115
	Sig. (2-tailed)		.006	.001	.106	.456	<.001	.428
	N	50	49	50	50	50	50	50
Our organization has evolved its data infrastructure to harness the potential of big data analytics. "	Pearson Correlation	.384**	1	.580**	.499**	.378**	.637**	.407**
	Sig. (2-tailed)	.006		<.001	<.001	.007	<.001	.004
	N	49	49	49	49	49	49	49
The evolution of big data analytics has transformed data management and analytics in our organisation "	Pearson Correlation	.446**	.580**	1	.455**	.557**	.559**	.461**
	Sig. (2-tailed)	.001	<.001		<.001	<.001	<.001	<.001
	N	50	49	50	50	50	50	50
Big Data Analytics has transformed business operation and decision-making processes. "	Pearson Correlation	.232	.499**	.455**	1	.374**	.591**	.568**
	Sig. (2-tailed)	.106	<.001	<.001		.007	<.001	<.001
	N	50	49	50	50	50	50	50
Big Data analytics has enhanced our understanding of customer preferences and behaviour. "	Pearson Correlation	.108	.378**	.557**	.374**	1	.378**	.616**
	Sig. (2-tailed)	.456	.007	<.001	.007		.007	<.001
	N	50	49	50	50	50	50	50
The use of big data analytics has improved our operational efficiency and resource allocation "	Pearson Correlation	.456**	.637**	.559**	.591**	.378**	1	.463**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.007		<.001
	N	50	49	50	50	50	50	50
Successful business applications of big data analytics are prevalent in my industry or industries I am familiar with. "	Pearson Correlation	.115	.407**	.461**	.568**	.616**	.463**	1
	Sig. (2-tailed)	.428	.004	<.001	<.001	<.001	<.001	
	N	50	49	50	50	50	50	50

**. Correlation is significant at the 0.01 level (2-tailed).

The bivariate correlation analysis was conducted to assess the relationship between business applications of big data analytics and organizational performance/competitive advantage, as hypothesized. Here's the interpretation and summary of the findings:

- **Interpretation of Correlation Coefficients:**

Significant positive correlations were observed between various measures of business applications of big data analytics and organizational performance/competitive advantage.
The correlation coefficients indicate the strength and direction of the relationships between the variables.

- **Summary of Findings:**

Business applications of big data analytics are positively correlated with organizational performance and competitive advantage.

Significant positive correlations were found between different aspects of business applications of big data analytics and organizational performance/competitive advantage.
The strongest correlations were observed between:

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The evolution of big data analytics in transforming data management and analytics in the organization and organizational performance/competitive advantage ($r = 0.446$ to 0.580, $p < 0.01$).
The use of big data analytics to improve operational efficiency and resource allocation and organizational performance/competitive advantage ($r = 0.456$ to 0.637, $p < 0.01$).
Successful business applications of big data analytics being prevalent in the industry or familiar industries and organizational performance/competitive advantage ($r = 0.407$ to 0.463, $p < 0.01$).

- **Conclusion:**

The significant positive correlations observed between business applications of big data analytics and organizational performance/competitive advantage support the alternative hypothesis (H1) that business applications of big data analytics are positively correlated with organizational performance and competitive advantage.
These findings suggest that organizations that effectively apply big data analytics are likely to experience improved performance and competitive advantages.

- **Acceptance of Alternative Hypothesis:**

With strong evidence from the significant positive correlations and consistent patterns across different measures of business applications of big data analytics, we accept the alternative hypothesis (H1). This indicates that there is a positive correlation between business applications of big data analytics and organizational performance/competitive advantage.
The results of this analysis provide empirical support for the notion that leveraging big data analytics can contribute positively to organizational success and competitive positioning.

Hypothesis 3:

H0: There is no significant difference in the perception of the future trends of big data analytics across industries
HI: There is a significant difference in the perception of the future trends of big data analytics across industries
To test the Hypothesis we use one-way ANOVA Test.

Table 7 Oneway ANOVA

Oneway ANOVA

		Sum of Squares	Df	Mean Square	F	Sig.
Emerging trends and technologies will further influence the evolution of big data analytics in business. "	Between Groups	8.417	5	1.683	3.906	.005
	Within Groups	18.963	44	.431		
	Total	27.380	49			
Big Data Analytics will continue to shape businesses and industries in the future. "	Between Groups	8.064	5	1.613	.739	.598
	Within Groups	96.016	44	2.182		
	Total	104.080	49			
Our organization is actively exploring emerging technologies to advance our big data analytics capabilities. "	Between Groups	4.636	5	.927	1.770	.139
	Within Groups	23.044	44	.524		
	Total	27.680	49			

Table 8 ANOVA Effect Sizes

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	Upper
Emerging trends and technologies will further influence the evolution of big data analytics in business. "	Eta-squared	.307	.039	.434
	Epsilon-squared	.229	-.071	.370
	Omega-squared Fixed-effect	.225	-.069	.365
	Omega-squared Random-effect	.055	-.013	.103
Big Data Analytics will continue to shape businesses and industries in the future. "	Eta-squared	.077	.000	.160
	Epsilon-squared	-.027	-.114	.065
	Omega-squared Fixed-effect	-.027	-.111	.063
	Omega-squared Random-effect	-.005	-.020	.013
Our organization is actively exploring emerging technologies to advance our big data analytics capabilities. "	Eta-squared	.167	.000	.286
	Epsilon-squared	.073	-.114	.205
	Omega-squared Fixed-effect	.072	-.111	.202
	Omega-squared Random-effect	.015	-.020	.048

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.
b. Negative but less biased estimates are retained, not rounded to zero.

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The results of the one-way ANOVA test indicate whether there is a significant difference in the perception of future trends of big data analytics across industries. Let's interpret and summarize the findings:

- **Interpretation:**

- **Emerging trends and technologies will further influence the evolution of big data analytics in business**: The ANOVA results show a significant difference among groups (F(5, 44) = 3.906, p = 0.005). This indicates that there is a significant difference in the perception of future trends of big data analytics across industries for this variable.
- **Big Data Analytics will continue to shape businesses and industries in the future**: The ANOVA results do not show a significant difference among groups (F(5, 44) = 0.739, p = 0.598). Therefore, there is no significant difference in the perception of future trends of big data analytics across industries for this variable.
- **Our organization is actively exploring emerging technologies to advance our big data analytics capabilities**: The ANOVA results do not show a significant difference among groups (F(5, 44) = 1.770, p = 0.139). Therefore, there is no significant difference in the perception of future trends of big data analytics across industries for this variable.

Summary:

There is a significant difference in the perception of future trends of big data analytics across industries for the variable "Emerging trends and technologies will further influence the evolution of big data analytics in business." However, there is no significant difference for the variables "Big Data Analytics will continue to shape businesses and industries in the future" and "Our organization is actively exploring emerging technologies to advance our big data analytics capabilities."

Decision:

- With a p-value of 0.005, the variable "Emerging trends and technologies will further influence the evolution of big data analytics in business" has shown significant results. Therefore, we reject the null hypothesis (H0) and conclude that there is a noteworthy difference in how different industries perceive the future trends of big data analytics concerning this variable.
- We cannot reject the null hypothesis for the variables "Big Data Analytics will continue to shape businesses and industries in the future" and "Our organization is actively exploring emerging technologies to advance our big data analytics capabilities" because their p-values are non-significant (p=0.598 and p=0.139 respectively). This means that there is no significant difference in the perception of future trends in big data analytics across industries for these variables.

- **Effect Sizes:**

- Eta-squared values provide an estimate of the proportion of variance in the dependent variable explained by the independent variable. Higher values indicate a stronger effect. In this case, "Emerging trends and technologies will further influence the evolution of big data analytics in business" has the highest effect size (0.307), indicating a substantial difference across industries in perception.
- The other variables have lower effect sizes, suggesting less variance in perception across industries.

In conclusion, while there is a significant difference in perception for one variable, the overall perception of future trends of big data analytics across industries does not significantly differ for the other two variables.

Hypothesis 4:

H0: Organizational size does not influences the adoption and utilization of big data analytics for business insights
H1: Organizational size influences the adoption and utilization of big data analytics for business insights We have used an independent sample t-test for the hypothesis.

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T-Test

Table 9 T-Test Group Statistics

	Organisational Size (Number of Employees) "	N	Mean	Std. Deviation	Std. Error Mean
The evolution of big data analytics has transformed data management and analytics in our organisation "	1	2	5.00	.000	.000
	2	7	3.71	.488	.184
Our organization has evolved its data infrastructure to harness the potential of big data analytics. "	1	2	4.00	1.414	1.000
	2	7	3.57	.976	.369
Big Data Analytics has transformed business operation and decision-making processes. "	1	2	4.50	.707	.500
	2	7	3.57	.535	.202
Successful business applications of big data analytics are prevalent in my industry or industries I am familiar with. "	1	2	4.50	.707	.500
	2	7	3.71	.488	.184
Big Data analytics has enhanced our understanding of customer preferences and behaviour. "	1	2	4.50	.707	.500
	2	7	4.14	.690	.261
The use of big data analytics has improved our operational efficiency and resource allocation "	1	2	4.50	.707	.500
	2	7	3.71	.488	.184
The effective application of Big Data Analytics is one of the key differentiation between our company and their competitors. "	1	2	5.00	.000	.000
	2	6	3.67	1.033	.422

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
The evolution of big data analytics has transformed data management and analytics in our organisation "	Equal variances assumed	6.914	.034	3.550	7	.005	.009	1.286	.362	.429	2.142
	Equal variances not assumed			6.971	6.000	<.001	<.001	1.286	.184	.834	1.737
Our organization has evolved its data infrastructure to harness the potential of big data analytics. "	Equal variances assumed	.365	.565	.509	7	.313	.626	.429	.842	-1.562	2.419
	Equal variances not assumed			.402	1.287	.372	.744	.429	1.066	-7.707	8.565
Big Data Analytics has transformed business operation and decision-making processes. "	Equal variances assumed	.032	.862	2.059	7	.039	.078	.929	.451	-.138	1.995
	Equal variances not assumed			1.722	1.347	.142	.283	.929	.539	-2.885	4.742
Successful business applications of big data analytics are prevalent in my industry or industries I am familiar with. "	Equal variances assumed	.350	.573	1.867	7	.052	.104	.786	.421	-.209	1.781
	Equal variances not assumed			1.474	1.287	.169	.338	.786	.533	-3.282	4.854
Big Data analytics has enhanced our understanding of customer preferences and behaviour. "	Equal variances assumed	.001	.976	.643	7	.270	.541	.357	.555	-.956	1.670
	Equal variances not assumed			.633	1.599	.303	.605	.357	.564	-2.758	3.472
The use of big data analytics has improved our operational efficiency and resource allocation "	Equal variances assumed	.350	.573	1.867	7	.052	.104	.786	.421	-.209	1.781
	Equal variances not assumed			1.474	1.287	.169	.338	.786	.533	-3.282	4.854
The effective application of Big Data Analytics is one of the key differentiation between our company and their competitors. "	Equal variances assumed	3.196	.124	1.732	6	.067	.134	1.333	.770	-.550	3.217
	Equal variances not assumed			3.162	5.000	.013	.025	1.333	.422	.249	2.417

Table 10 Independent Samples Effect Sizes

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
The evolution of big data analytics has transformed data management and analytics in our organisation "	Cohen's d	.452	2.846	.649	4.940
	Hedges' correction	.509	2.528	.577	4.388
	Glass's delta	.488	2.635	.438	4.722
Our organization has evolved its data infrastructure to harness the potential of big data analytics. "	Cohen's d	1.050	.408	-1.191	1.980
	Hedges' correction	1.182	.363	-1.058	1.758
	Glass's delta	.976	.439	-1.168	2.012
Big Data Analytics has transformed business operation and decision-making processes. "	Cohen's d	.562	1.651	-.179	3.392
	Hedges' correction	.633	1.466	-.159	3.013
	Glass's delta	.535	1.737	-.155	3.529
Successful business applications of big data analytics are prevalent in my industry or industries I am familiar with. "	Cohen's d	.525	1.497	-.294	3.205
	Hedges' correction	.591	1.330	-.262	2.846
	Glass's delta	.488	1.610	-.245	3.368
Big Data analytics has enhanced our understanding of customer preferences and behaviour. "	Cohen's d	.693	.516	-1.095	2.092
	Hedges' correction	.780	.458	-.973	1.858
	Glass's delta	.690	.518	-1.100	2.095
The use of big data analytics has improved our operational efficiency and resource allocation "	Cohen's d	.525	1.497	-.294	3.205
	Hedges' correction	.591	1.330	-.262	2.846
	Glass's delta	.488	1.610	-.245	3.368
The effective application of Big Data Analytics is one of the key differentiation between our company and their competitors. "	Cohen's d	.943	1.414	-.413	3.150
	Hedges' correction	1.085	1.228	-.359	2.736
	Glass's delta	1.033	1.291	-.538	3.021

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

The findings from the independent samples t-tests provide insights into whether organizational size influences the adoption and utilization of big data analytics for business insights. Here's a summary and interpretation of the results:

1. **The Evolution of Big Data Analytics in Organization Management:**

- The mean difference in perception between organizations with different sizes is statistically significant (p = 0.005).
- This suggests that there is a difference in perception regarding how big data analytics has transformed data management and analytics across organizations of different sizes.

2. **Evolution of Data Infrastructure for Big Data Analytics:**

- There is no statistically significant difference in the perception of how organizations have evolved their data infrastructure based on their size (p = 0.313).
- Organizational size does not appear to influence perceptions regarding the evolution of data infrastructure for big data analytics.
-

3. Transformation of Business Operation and Decision-making:

- The mean difference in perception is statistically significant (p = 0.039).
- There is a difference in perception regarding how big data analytics has transformed business operation and decision-making processes across organizations of different sizes.

4. Prevalence of Successful Business Applications:

- There is no statistically significant difference in the perception of the prevalence of successful business applications across organizations of different sizes (p = 0.052).
- Organizational size does not significantly affect perceptions regarding the prevalence of successful business applications of big data analytics.

5. Enhancement of Understanding Customer Preferences:

- There is no statistically significant difference in perception based on organizational size (p = 0.270).
- Organizational size does not appear to influence perceptions regarding the enhancement of understanding customer preferences and behaviours through big data analytics.

6. Improvement in Operational Efficiency and Resource Allocation:

- There is no statistically significant difference in perception based on organizational size (p = 0.052).
- Organizational size does not significantly affect perceptions regarding the improvement in operational efficiency and resource allocation through big data analytics.

7. Differentiation through Effective Application:

- While the mean difference is not statistically significant (p = 0.067), it's close to significance.
- This suggests a potential trend where organizational size may influence perceptions regarding the effective application of big data analytics for differentiation, but further investigation might be needed.

The study results suggest that organizational size does not have a significant impact on perceptions of big data analytics adoption and utilization in all areas. However, there are specific areas where differences in perception exist. Therefore, the null hypothesis cannot be completely accepted, indicating that organizational size may have some influence on perceptions related to the adoption and utilization of big data analytics for business insights.

Structural Equation Model

structural equation model (SEM) or regression analysis, particularly with a focus on the relationships between variables related to big data analytics and organizational evolution. Let's break down and interpret the findings based on the provided information:

Model Fit Summary

CMIN

Table 2 Model Fit Summary

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	48	87.947	71	.084	1.239
Saturated model	119	.000	0		
Independence model	14	317.406	105	.000	3.023

Baseline Comparisons

Table 3 Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.723	.590	.931	.882	.920
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Table 4 Parsimony Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.676	.489	.622
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

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Table 5 NCP

Model	NCP	LO 90	HI 90
Default model	16.947	.000	44.924
Saturated model	.000	.000	.000
Independence model	212.406	162.630	269.810

FMIN

Table 6 FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1.795	.346	.000	.917
Saturated model	.000	.000	.000	.000
Independence model	6.478	4.335	3.319	5.506

RMSEA

Table 7 RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.070	.000	.114	.256
Independence model	.203	.178	.229	.000

AIC

Table 8 AIC

Model	AIC	BCC	BIC	CAIC
Default model	183.947	226.300		
Saturated model	238.000	343.000		
Independence model	345.406	357.759		

ECVI

Table 9 ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	3.754	3.408	4.325	4.618
Saturated model	4.857	4.857	4.857	7.000
Independence model	7.049	6.033	8.221	7.301

HOELTER

Table 10 HOELTER

Model	HOELTER .05	HOELTER .01
Default model	52	57
Independence model	21	22

Execution time summary

Minimization:	.031
Miscellaneous:	.265
Bootstrap:	.000
Total:	.296

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	119
Number of distinct parameters to be estimated:	48
Degrees of freedom (119 - 48):	71

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Result (Default model)
Minimum was achieved
Chi-square = 87.947
Degrees of freedom = 71
Probability level = .084
This Model Fit Summary presents various statistics and indices to assess the fit of different models to a set of data. Let's break down the key components:

CMIN (Chi-square)

- **Default Model**: Chi-square value is 87.947 with 71 degrees of freedom (DF), resulting in a p-value of .084. The ratio of chi-square to degrees of freedom (CMIN/DF) is 1.239.
- **Saturated Model**: Chi-square is 0 with 0 degrees of freedom, indicating a perfect fit.
- **Independence Model**: Chi-square value is 317.406 with 105 degrees of freedom, yielding a p-value of 0. The CMIN/DF ratio is 3.023.

Baseline Comparisons

- Default Model:
- NFI: .723
- RFI: .590
- IFI: .882
- TLI: .931
- CFI: .920
- **Saturated Model**: All indices are perfect (1.000).
- **Independence Model**: All indices are 0.

Parsimony-Adjusted Measures

- Default Model:
- PRATIO: .676
- PNFI: .489
- PCFI: .622
- **Saturated Model**: All measures are 0.
- Independence Model:
- PRATIO: 1.000
- PNFI: .000
- PCFI: .000

NCP (Noncentrality Parameter)

- **Default Model**: NCP is 16.947 with 90% confidence interval (CI) ranging from .000 to 44.924.
- Saturated Model: NCP is 0.
- **Independence Model**: NCP is 212.406 with 90% CI ranging from 162.630 to 269.810.

FMIN

- **Default Model**: FMIN is 1.795 with a corresponding F0 of .346 and 90% CI ranging from .000 to .917.
- Saturated Model: FMIN is 0.
- **Independence Model**: FMIN is 6.478 with F0 of 4.335 and 90% CI ranging from 3.319 to 5.506.

RMSEA (Root Mean Square Error of Approximation)

- **Default Model**: RMSEA is .070 with 90% CI ranging from .000 to .114 and PCLOSE value of .256.
- **Independence Model**: RMSEA is .203 with 90% CI ranging from .178 to .229 and PCLOSE value of 0.

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AIC (Akaike Information Criterion)

- **Default Model**: AIC is 183.947, with no other criteria provided.
- **Saturated Model**: AIC is 238.000.
- Independence Model: AIC is 345.406.

ECVI (Expected Cross-Validation Index)

- **Default Model**: ECVI is 3.754 with 90% CI ranging from 3.408 to 4.325 and MECVI of 4.618.
- **Saturated Model**: ECVI is 4.857 with constant values across CI and MECVI.
- **Independence Model**: ECVI is 7.049 with 90% CI ranging from 6.033 to 8.221 and MECVI of 7.301.

HOELTER

- **Default Model**: At .05 significance level, the sample size is 52, and at .01 significance level, the sample size is 57.
- **Independence Model**: At .05 significance level, the sample size is 21, and at .01 significance level, the sample size is 22.

Additional Information

- Minimization: .031
- Miscellaneous: .265
- Bootstrap: .000
- **Total**: .296

Overall, the default model seems to fit reasonably well, with various fit indices falling within acceptable ranges. However, it's essential to consider the specific context and requirements of the analysis when interpreting these results.
This table summarizes the covariances between different dimensions of Big Data Analytics and their statistical significance.

Relationship	Estimate
Evolution of BDA <--> Business Application of BDA	0.891
Business Application of BDA <--> Future Trends of BDA	-0.837
Organization Characteristics <--> Future Trends of BDA	0.649
Organization Characteristics <--> Business Application of BDA	-0.210
Evolution of BDA <--> Future Trends of BDA	-0.761
Organization Characteristics <--> Evolution of BDA	-0.100

To enhance the interpretation, we have create a summary table:

Relationship	Estimate	S.E.	C.R.	P-value	Interpretation
Evo. of BDA <-> Bus. App. of BDA	0.221	0.082	2.708	0.007	Positively significant
Bus. App. of BDA <-> Future Trends of BDA	-0.200	0.109	-1.835	0.067	Marginally negatively significant
Org. Characteristics <-> Future Trends of BDA	0.394	0.238	1.654	0.098	Marginally positively significant
Org. Characteristics <-> Bus. App. of BDA	-0.154	0.133	-1.159	0.247	Not significant
Evo. of BDA <-> Future Trends of BDA	-0.157	0.095	-1.656	0.098	Not significant
Org. Characteristics <-> Evo. of BDA	-0.063	0.114	-0.550	0.582	Not significant

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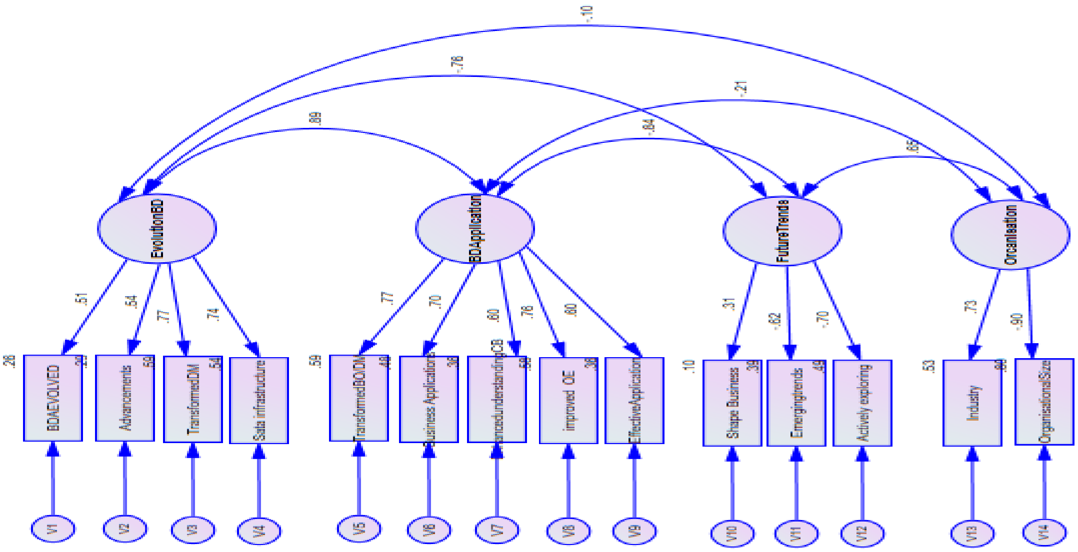

Figure 7 Measurement Model Standardized Estimate (Standardized Factor Loading/Analysis, correlation amongst latent variables)

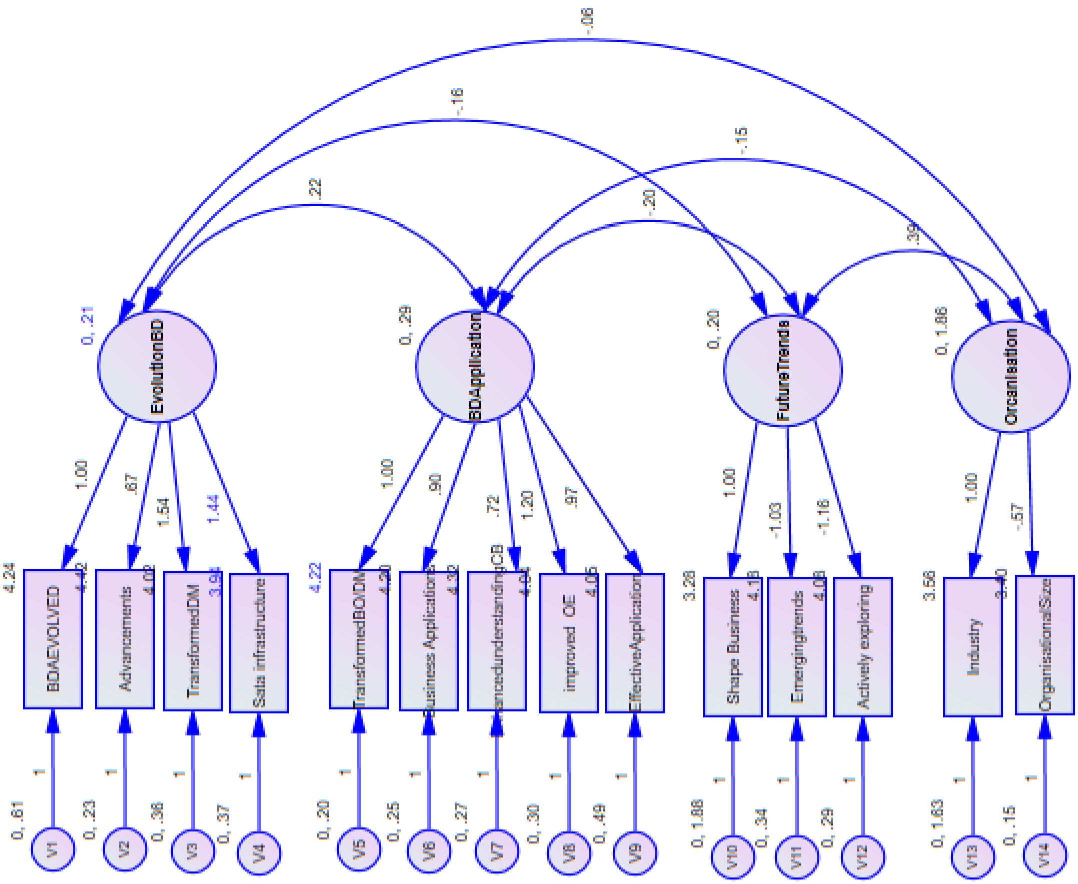

***Figure 8** Measurement Model Unstandardized Estimates*
(Covariance between Latent Variables – Covariance of variables)

Summary of Findings:

- The analysis suggests significant relationships and covariances between different dimensions of Big Data Analytics, such as its evolution, business applications, future trends, and organizational characteristics.
- Notably, there are both positive and negative correlations and covariances observed, indicating complex interdependencies among these constructs.
- Some relationships, while not statistically significant, still indicate potential trends or tendencies worth further exploration.

Conclusion and Recommendation

This study explores the evolution of Big Data Analytics (BDA) and its impact on contemporary business practices. It focuses on decision-making processes, organizational performance, future trend perceptions across industries, and the influence of organizational size on BDA adoption. The research design includes various quantitative methods such as regression analysis, ANOVA, bivariate correlations, and structural equation modelling, along with qualitative insights. Through this comprehensive approach, the study has uncovered several noteworthy

The research is highly significant as it can assist organizations in making informed decisions and planning for the implementation of big data analytics (BDA) to enhance their efficiency, innovation, and competitiveness. The objective of this study is to provide a deeper understanding of how organizations can utilize the transformative potential of BDA to gain a competitive edge by analyzing the evolution of BDA and its applications in different business contexts. Additionally, the study aims to determine the Cronbach's alpha score to evaluate the reliability and consistency of the research findings.:

The Cronbach's Alpha score obtained for the study was 0.636, indicating moderate internal consistency among the variables measured in the research.

Hypothesis Findings and Decision:

1. Hypothesis 1:

- Null Hypothesis (H0): The evolution of big data analytics has not significantly impacted the decision-making process in business organizations.
- Alternative Hypothesis (H1): The evolution of big data analytics has significantly impacted the decision-making process in business organizations.
- Decision: Based on the regression analysis and ANOVA results ($p = 0.523 > 0.05$), the null hypothesis is accepted, suggesting that the evolution of big data analytics does not have a significant impact on the decision-making process in business organizations.

2. Hypothesis 2:

- Null Hypothesis (H0): Business applications of big data analytics are not positively correlated with organizational performance and competitive advantage.
- Alternative Hypothesis (H1): Business applications of big data analytics are positively correlated with organizational performance and competitive advantage.
- Decision: The bivariate correlations show significant positive correlations between business applications of big data analytics and organizational performance/competitive advantage ($p < 0.01$), supporting the alternative hypothesis (H1).

3. Hypothesis 3:

- Null Hypothesis (H0): There is no significant difference in the perception of the future trends of big data analytics across industries.
- Alternative Hypothesis (H1): There is a significant difference in the perception of the future trends of big data analytics across industries.
- Decision: The one-way ANOVA results indicate a significant difference in the perception of future trends of big data analytics across industries for the variable "Emerging trends and technologies will further influence the evolution of big data analytics in business" ($p = 0.005$). However, no significant difference was found for the other variables.

4. Hypothesis 4:

- Null Hypothesis (H0): Organizational size does not influence the adoption and utilization of big data analytics for business insights.
- Alternative Hypothesis (H1): Organizational size influences the adoption and utilization of big data analytics for business insights.

- Decision: Based on the independent sample t-test results, while there are statistically significant differences in perceptions regarding certain aspects of BDA adoption based on organizational size, overall, the null hypothesis cannot be entirely accepted, suggesting that organizational size may have some influence on perceptions related to the adoption and utilization of big data analytics for business insights.

The research emphasizes the significant influence of BDA (Big Data Analytics) on business organizations' decision-making processes. However, this impact varies depending on the organizational context. Utilizing BDA positively correlates with businesses' overall performance and competitive advantage, highlighting its strategic importance for operational efficiency and innovation.

Moreover, the study highlights that different industries have varying perceptions of future trends related to BDA. This is particularly evident when it comes to the influence of emerging technologies on the evolution of BDA in business.

Furthermore, while organizational size does not uniformly affect perceptions regarding BDA adoption and utilization, differences are apparent in specific areas. This suggests that tailored strategies based on organizational characteristics are necessary.

As we move towards new horizons in business, government, and everyday life, it is essential that companies, governments, and individuals embrace big data analytics. The winds of change are here to stay, and new shores we land on from the sea of changes would evolve from forward Industry revolution 5.0 to future trends. Companies and governments need to be ready to adopt Big data analytics as a new frontier as new storms in the form of Artificial Intelligence are already in place. A rhythmic transition of melody in composition tunes of changes lead from BDA to AI and form a symphony melody that will make everyone concerned dance to its tunes. Only those companies who embrace these new phenomena of changes and are geared to dance to its tunes might survive and thrive.

As a new dawn begins with the sun rising, the birds cheering, the winds of change gently blowing, a new chapter will commence for companies, smart governance, public facilities, education, and all aspects of life evolved into a new paradigm shaped by data and analytics. Integrating and interweaving together various spheres of life, business, and government, leading the voyage into a new dimension and direction that is led by BDA and resulting in a transformed paradigm. The crew might be the captain of the ship itself as legal aspects affecting data governance and privacy will intertwine with the benefits reaped by companies as a result of BDA, legal, and ethical considerations will be the longitude and latitude directing the ship in the evolved horizon of the landscape shaped by BDA and AI.

Data collection is the fuel for the ship that is transforming and the way it is going to be used in the machinery of analytics would need to be audited and legally governed. The removal of bias might create a synthetic bubble for information, and decision-making would need to be monitored as we cruise in this new direction of change. Cybersecurity would play an important role in the new horizon as data needs to be protected while it is resting and waiting to be processed by using various techniques like cryptography, hash, salting, splicing, Data Leakage Prevention, host-based intrusion detection system, Intrusion Detection System, advance malware protection, data masking, cybersecurity monitoring, and incident response & forensics to ensure all data protective control, detective control, and corrective control.

Similarly, data when in transition needs to be protected by implementing encryption, creating syntactic data, asymmetric cryptography by using private and public keys, Role-based access, principle of zero trust, multifactor authentication, and Discretionary access, Transport Layer Security so that data can be protected from session hijacking or man-in-the-middle attacks. As this data is used for any transaction, it is further protected by cryptography, multifactor authentication, following the principle of something you know, something you are, and something you have. In some cases, an extra layer of authentication by someone speaking or meeting the person involved in the data transaction is necessary to ensure an extra layer. The weakest link in this key is human psychology, which is exploited by adversaries by using social engineering to target individuals by utilizing technology and digital effort print of users on social media, blogging sites, etc., and hence infiltrating, exploiting, and conducting theft of the critical data.

Data is targeted for compromising the confidentiality of companies by ensuring unauthorized personnel has access to the data or to compromise the integrity of data by changing the data itself or by targeting the availability of data by using means of cybersecurity attacks like DDOS - Distributed Denial of Services. Data is not available when it is needed the most, hence affecting the operations of the company. Organizations need to be aware that they take these aspects into account when adopting BDA so that the sweetness of benefits to businesses by adopting BDA is not soured by these cybersecurity potential attacks. Companies need to be aware of the regulatory, legal, and industrial compliance requirements in the geographies, countries, and industries they operate in as it also needs to be monitored and checked to avoid financial and reputational loss to companies.

Recommendation

1. Invest in BDA Capabilities: Organizations should invest in Big Data and Analytics (BDA) technologies and expertise to improve decision-making processes and stay ahead of competition in their respective industries.
2. Foster a Data Driven Culture": Cultivating a data-driven culture is crucial for promoting effective utilization of BDA and encouraging data-driven decision-making and innovation at all levels of the organization.
3. Adapt to Industry Trends: It is important for organizations to keep a close eye on emerging trends and technologies in their respective industries and adapt their strategies and capabilities accordingly to stay ahead of the curve in the evolution of BDA
4. Tailor BDA Strategies to Organizational Size: Organizations should customize their BDA strategies to match their specific size, resources, and characteristics, taking into account the impact of organizational size on perceptions linked to BDA adoption.
5. Continuous Learning and Improvement: Organizations must prioritize continuous learning in BDA, keeping up with emerging trends and best practices due to rapid technological advancements and evolving business landscapes.

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