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Impact of Big Data Analytics on Indian E-Tailing from SCM to TCS

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Abstract

Purpose: The study aims to recognize the relationship between big data analytics capabilities, big data analytics process, and perceived business performance from supply chain management to total customer satisfaction. **Research design, data and methodology:** The study followed a quantitative approach with a descriptive design. The data was collected from leading e-commerce companies in India using a structured questionnaire, and the data was coded and decoded using MS Excel, SPSS, and R language. It was further tested using Cronbach's alpha, KMO, and Bartlett's test for reliability and internal consistency. **Results:** The results showed that the big data analytics process acts as a robust mediator between big data analytics capabilities and perceived business performance. The 'direct, indirect and total effect of the model' and 'PLS-SEM model' showed that the big data analytics process directly impacts business performance. **Conclusions:** A complete indirect relationship exists between big data analytics capabilities and perceived business performance through the big data analytics process. The research contributes to e-commerce companies' understanding of the importance of big data analytics capabilities and processes.

Keywords: Big Data Analytics, E-tailing, Big Data Analytics Capabilities, Big Data Analytics Process, Business Performance, Supply Chain Management (SCM), Total Customer Satisfaction (TCS)

JEL Classification Code : L81, M31, N35

1. Introduction

The Internet penetration rate in India increased to nearly 48.7 % in 2022, compared to four percent in 2007, indicating that almost half of the country's population has access to the Internet. (Statista, 2023). With the growth of Internet users, customer perception towards shopping has drastically changed. The retail industry has acknowledged drastic changes in the dynamic business scenario supported by technology. The number of online buyers in India is expected to reach 500 million in 2030 from 150 million in 2020. The Indian E-commerce market is expected to reach 350 billion USD in GMV by 2030. (Indian Brand Equity Foundation, 2023). Electronic retailing (e-tailing, e-retailing, Internet retailing, online retailing) sells retail goods using the Internet. It relates to the business-to-consumer (B2C) sale of retail goods over the Internet (Kautish et al., 2021). The Internet has transformed e-tailing (online retailing), and

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buyers now can access a wide range of products offered by several e-tailing companies. This has steered to a paradigm shift in the e-tailing business, where firms face challenges in developing capabilities and creating processes that can lead to better business performance. The research studied the Indian e-tailing sector's business performance from their supply chain management activities to create complete customer satisfaction. This covers online buying behavior and physical distribution of goods and services. A similar research study was initiated based on the Indian retailing industry supply chain activities and customer satisfaction (Potluri & Kaiaru, 2023). Correspondingly, e-tailing firms are facing the challenge of explicitly identifying online purchase benefits and factors influencing customer satisfaction that can lead to recommendations and repurchases. The e-tail industry has created great interest due to the voluminous variety and velocity of data being used for analysis, and the e-tailers use big data analytics for analyzing customers' data to gain more significant insights on consumer buying behavior, personalized offers, and increased gross margins (Savitz, 2012). Big data analytics inspects the massive amount of data to uncover valuable hidden patterns, correlations, and other insights. It refers to "technologies and techniques used to analyze large-scale and complex data to help enhance a firm's performance" (Kwon et al., 2014). The current research tested the impact of big data analytics on e-tail business performance from the perspective of e-tail firms. The study was conducted by collecting data from representatives of e-tailing companies in the positions of think-tank administrators and technical departments. The results indicated that the 'big data analytics process' is an essential mediator positively impacting e-tail business performance. Based on the contemporary significance of e-tailing and big data analytics, the researchers have initiated the current study to explore and analyze the factors that influence the e-tailing businesses of India by applying big data analytics.

2. Literature Review and Hypotheses

The Indian retail industry has emerged as a fast-paced and dynamic sector due to the entry of new players into the market. Retailing accounts for 10 % of the country's gross domestic product, has offered employment to 8 % of the workforce, and is expected to create 25 million new jobs by 2030. India is the fifth most prominent destination in the retail space. The sector attracted US$ 4.48 billion in FDIs between April 2000 and June 2023 due to the potentiality and growth rate (Indian Brand Equity Foundation, 2023). The Indian retail industry is classified into organized and unorganized sectors. The organized retail market has a share of 12 percent of the total market and has a growth rate of 10 percent from 2021 to 2032. There are plenty of reasons for such kind of whooping growth of the Indian retail sector, like the wealth of resources, the largest populated country in the world, the increasing trend of micro-families, urbanization, the spread of retailing even to small and medium-sized cities, availability of low-cost labor, healthy economic growth, changing demographic profile of country's population, a snowballing trend of disposable income, government support, and most significantly evolving consumer tastes and preferences. Along with these, other reasons include the growth of the information technology sector, infrastructural facilities, acculturation, awakening the sleeping giant-Indian rural market, and extensive generations Y and Z growth.

Developments in Information technologies (IT) and electronic commerce (E-Commerce) have enabled drastic shifts in organizations in the markets (Kim et al., 2018). E-commerce, defined as buying and selling goods or services over a computer network using the Internet, has significantly changed the business landscape (Eurostat, 2017). E-commerce opens potential opportunities for retailing firms by offering access to a wide range of customers and reducing the cost of dealing with these (Colton et al., 2010). The Indian e-commerce sector has witnessed steep growth in the last decade and a half based on levers such as enhanced smartphone penetration, decreasing Internet data prices, and telecom companies' quality services. India is the world's second-largest Internet market, with over 45 billion UPI transactions worth over a trillion US dollars in the financial year 2021-22 (Invest India, 2022). In the financial year 2023, the value of UPI-based digital payments in India was over US$ 1.67 trillion, with over 83 billion UPI transactions (Statista, 2023). The Internet penetration in India as of March 2023 is over 880 million, and the number of telecom subscribers as of March 2023 is over 1172 million (TRAI, 2023). The e-commerce market is expected to touch US$ 350 billion in gross merchandise value by 2030, and as of 2021, there were 1.2 million daily e-commerce transactions. The country's online shoppers are expected to reach 500 million in 2030 (Indian Brand Equity Foundation, 2023).

In this digital age, data is generated and available everywhere, and organizations in all sectors are inevitably dealing with big data. (Sheng et al., 2017; Corte-Real et al., 2017). Big data is often used to designate a large amount of structured, semi-structured, and unstructured data available for real-time processing (Sheng et al., 2017; Ferraris et al., 2019). Big data refers to data whose volume, velocity, and variety make it challenging for an organization to handle, analyze, and derive meaningful insights using traditional processing methods (Manyika et al., 2011). Analytics is extracting meaningful insights from the data by generating reports using statistical and mathematical models

(Grossman & Siegel, 2014). The renowned organization Theorist and Author Geoffrey Moore highlighted the significance of big data analytics with the sentence, "Without big data analytics, companies are blind and deaf, wandering out onto the web like deer on a freeway." The theoretical background depicts that big data analytics are increasingly significant to strategic and management decision-making (Chen et al., 2012; La Valle et al., 2011). Big data analytics is "technologies and techniques used to analyze large-scale and complex data to help enhance a firm's performance" (Kwon et al., 2014). Russom (2014) defines "big data analytics as the application of advanced analytic techniques on larger datasets." The concept is explained comprehensively as "a workflow which filters terabytes of low-value data down into more granular data of high value" (Fisher et al., 2012).

The use of big data analytics in organizations is generally considered to improve organizational performance. Organizational performance depends on the capabilities of organizations to provide the required resources for applying big data analytics. (Kibe et al., 2020). According to Al-Sakran (2014), using big data analytics, an e-commerce firm may learn to predict buyers' negotiation strategies and develop tactics to achieve performance in their best interests. Big data analytics is essential because it enhances an organization's ability to interconnect technology and the end-users/customers (Brown et al., 2011; Dobusch & Kapeller, 2018), thus enabling organizations to manage and convert data into meaningful information and use it as a critical differentiator contributes to its success (Papadopoulos et al., 2017). E-commerce firms need to use big data analytics as they have better prospects to interact with customers frequently in real-time than the firms that do not have (Akter & Wamba, 2016). It enables e-commerce firms to use data more efficiently, drive a higher conversion rate, improve decision-making, and empower customers.

The most significant challenge is to generate business value from the disruption of big data (Olabode et al., 2022). Among the 5V's of big data, velocity, volume, and variety (Johnson et al., 2017) are used as a common framework to explain big data, differentiate big data and big data analytics, which relies on the creation, storage and the use of these data (Lanzolla & Giudici, 2017). Volume and variety refer to significantly large amounts and types of data (from varied sources), and velocity refers to the rapid pace at which the data is generated (Johnson et al., 2017). Veracity represents the undependability inherent in specific data sources that require analysis to gain dependable predictions (Gandomi & Haider, 2015). Lastly, term value implies the generation of economically sound insights and benefits by analyzing the data through extraction and transformation (Wamba et al., 2015). Adding to the definition, other researchers can term the business value of big data as the transactional, informational, and strategic benefits for e-commerce firms (Wixom et al., 2013). Here, the transactional value focuses on enhancing efficiency and reducing costs; informational value throws light on real-time decision-making, and strategic value deals with attaining competitive advantage. Big data analytics offers more significant insights that can be used to enhance dynamic capabilities by helping organization decision-makers respond to fast-changing market trends (Erevelles et al., 2016; Eisenhardt & Martin, 2000). When the potential of big data analytics is harnessed, the insights obtained will improve the organization's performance and create value (Bharadwaj et al., 2013; Ferraris et al., 2019).

The application of big data in e-commerce is helpful in personalization or customization, dynamic pricing, customer service, predicting consumer behavior, supply-chain visibility, and managing fraudulent activities (Akter & Wamba, 2016). According to a study on 'Investment in Hadoop Analytics,' there was greater labor productivity and customer responsiveness than others who didn't (Tambe, 2014). Using big data technologies can increase the returns on management activities by developing more significant insights derived from interaction with suppliers, customers, and competitors. Using such technologies helps e-tailers offer a better customer experience through personalized recommendations, simplified processes, and improved experience (Gauri et al., 2021). Due to the pandemic, substantial developments and changes in electronic commerce have been observed during the quinquennium. The same is emphasized in the chapter of the book published in the context of the United Arab Emirates (Potluri & Thomas, 2023). Compared to before the pandemic, the customer intention to buy products using e-commerce sites has significantly increased across all the categories (Chang & Chen, 2021). Subsequently, e-commerce companies have drastically re-engineered business at every level. However, the uncertainty on revenue and business models of e-commerce firms prompts them to consider investments carefully. As profit margins are shrinking, e-commerce firms must focus on optimizing the cost of business operations and keep assessing the impact of big data analytics on a firm's performance from the company's point of view. The linkage between data analytics and marketing and customer analytics is evidently and substantially explained in the book chapter (Potluri & Muuka, 2021). The application and acceptance challenges of big data analytics in Indian micro, small, and medium enterprises are enunciated in another book chapter (Potluri, 2022).

A theoretical model is a higher level of explaining the phenomena based on theoretical understandings. Concerning Figure 1, this study conceptualized and understood the relation among constructs, namely, big data analytics capabilities and their process and perceived business performance from the company representative's perspective; this was not attempted earlier in the Indian context. The big data analytics capabilities comprise an organization's techniques and processes to enable the organization to process, analyze, and visualize the big data, thereby offering meaningful insights and helping decision-making (Akter et al., 2016; Dubey et al., 2018). From the review of the literature, the researchers used various approaches to assess big data analytics capabilities as a unidimensional construct (Dubey et al., 2018, 2019; Srinivasan & Swink, 2018) or as a higher-order construct comprising different dimensions (Akter et al., 2016; Wamba et al., 2017; Gupta et al., 2019).

The following are the conceptual and operational definitions of various constructs used in the research: Big data analytics refers to critical organizational capabilities to provide business insights leading to a sustainable competitive advantage in a big data environment with 18 items. All these items were measured on a 5-point Likert scale, with one (1) strongly disagreeing and five (5) strongly agreeing. The big data analytics process refers to the extent to which a firm can acquire the necessary competencies for making data-driven decisions, predicting trends, focused marketing, automating business processes, and developing customer relationships, having nine items, measured in five (5) point rating scale, one (1) strongly disagrees, and five (5) strongly agrees. Business Performance (PERF) refers to an organization's ability to acquire and retain customers and increase sales, profitability, and return on investment. Ten items were measured. Five items are meant for measuring financial performance, and five for market performance. Each item is measured on five (5) a point rating scale: one (1) is strongly disagree, and five (5) is strongly agree. While it is well recognized that big data analytics capabilities can enhance an organization's performance (Akter et al., 2016; Wang et al., 2019; Dubey et al., 2019), the researchers also pay attention to how the big data analytics process interacts with business performance.

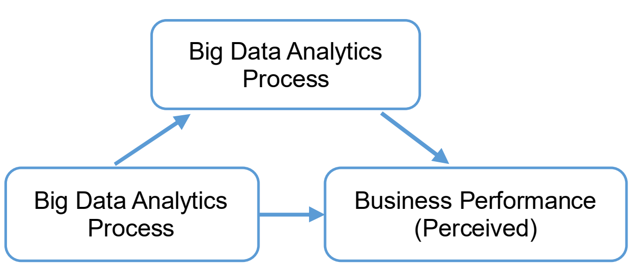

Figure 1: Theoretical Model – E-tailing Company representatives' perspective.

The researchers selected the following hypotheses for an in-depth study of the set objectives based on the extensive literature review and theoretical framework.

Research hypotheses

H1$_1$. Big data analytics capabilities are related to the big data analytics process.

H2$_1$. A higher big data analytics process will positively contribute toward higher perceived business performance.

H3$_1$. The big data analytics process mediates between big data analytics capabilities and perceived business performance.

H4$_1$. Big data analytics capabilities have a direct effect on perceived business performance.

H5$_1$. Use of big data analytics positively impacts e-tail business performance.

3. Aims

This paper aims to investigate how big data analytics impacts e-tailing business performance from the Indian context and to answer the role of the big data analytics process as a mediator between big data analytics capabilities and perceived business performance.

4. Methodology

This section deals with methodology aspects, including research approach, statement of the problem, research questions, objectives, the scope of the study, design and method of the study, sample design, questionnaire construction, data collection methods and sources, statistical tools, and techniques, and software used for data analysis. Likert five-point scale was used in the research.

4.1. Research Method

To lay a strong foundation for the research, the literature was reviewed exhaustively in the relevant area of study, covering investigations from the recent past. Initially, research papers with concerned titles were chosen. Secondly, papers related to the broader area of study were selected. Thirdly, articles and papers assimilated through forward and backward citation were chosen. Lastly, articles, literature, surveys, opinions, interviews, and company reports published online were considered. Before conducting the final survey, a pilot study was conducted to check the reliability and validity of the research instruments. Researchers met industry experts for discussions during research and collected opinions on the topic. The initial plan was to cover company representatives from at least twelve e-tailers in India who have implemented big data. However, the lack of credentials and responses filtered down coverage to select seven e-tailers. An extensive literature review identified the following research gaps to study the effects of big data analytical capabilities and analytics processes on perceived business performance from e-tailing companies' perspectives.

4.2. Statement of the Problem

The Internet has transformed e-tailing (online retailing), and buyers can now access a wide range of products offered by several e-tailers. This has steered to a paradigm shift in the e-tailing business where firms face challenges in developing capabilities and creating a process that can lead to Business Performance. This paper investigates how big data analytics impacts e-tailing business performance from the Indian context.

4.3. Research Questions

RQ1. What factors affect big data analytics capabilities from company representative perspectives?

RQ2. How does a relation exist between big data analytics capabilities and perceived business performance?

a. Are big data analytics capabilities antecedents of the big data analytics process?
b. Does the big data analytics process lead to perceived business performance?
c. Is there any relationship between big data analytics capabilities and perceived business performance?
d. Does a direct relationship exist between big data analytics capabilities and perceived business performance, or is there an indirect relationship between big data analytics capabilities and perceived business performance through the big data analytics process?

4.4. Objectives

1. To identify and analyze the factors that affect the big data analytics capabilities of e-tailing companies.
2. To evaluate the role of the big data analytics process as a mediator between big data analytics capabilities and perceived business performance.
3. To validate the impact of big data analytics on e-tailing business performance.

4.5. Scope

The scope of the study covers only e-tailing companies in India. It covers only e-tailing aspects, i.e., selling products online (not services) that includes 'Business to Consumers'. It focuses on using big data analytics (BDA) applications in e-tailing companies and their impact on business performance. The focus is researching 'e-tailing company representatives'. It does not cover other parties/elements involved in the ecosystem, like suppliers and banks. The domain scope covers constructs that are relevant to big data analytics capabilities, big data analytics processes, and perceived business performance. The data is the cross-section data, i.e., one-time only. It is the sign of the magnitude of the relationship or causality but not causality itself. The term' company representatives' refers to potential contributors for this research representing select e-tailing companies in India with the designations of CEO/MD/VP/Director, CTO/CIO, Managers/Leads, Data Scientists, Big Data Architects, and Analysts.

4.6. Design and Method

The design and method of the study determine the valuable outcomes of the research. The study followed a quantitative research approach and adopted a descriptive design, which tried to answer how big data analytics capabilities work through the big data process on performance; a survey research strategy or method was employed.

4.7. Data Collection Methods and Sources

Data was collected using a questionnaire from the primary source. Though the survey cannot establish causality, it can ensure external generalizability and indirectly indicate the sign of causality. Since the study aimed to test the theory prevailing in the big data literature, the study followed deductive logic, which was meant to test the theory and then move from general theory to particular data. The researchers collected all kinds of information for this research based on both primary and secondary sources. The data was collected from the primary source using an online questionnaire (Google Docs) and hard-copy questionnaires from e-tailing company representatives. Secondary sources of data collection have been collected by extensively reviewing the literature from journals, online websites, web postings, newspapers, online articles, and publications and discussing it with industry experts. The researchers administered a non-probability, convenient sampling method. They collected the opinions of e-tailing company representatives with a self-administered and well-structured questionnaire via LinkedIn, phone calls, WhatsApp, and emails. Questionnaires were sent to about 350 company representatives from 12 different e-tailing companies, of which 82 responded from seven companies. After filtering the responses (12 out of scope), it was brought down to 70 responses from seven e-tailing companies.

Positive aspects of data collection: Personal and professional contacts played a vital role, and their contribution was significant during the pilot study. After a few iterations, the questionnaire was finalized. During the pilot study, these measures established a Cronbach alpha of more than 0.7. The subsequent section dealt with the data analytics process; this is a customized scale borrowed from the pilot study and demonstrated Cronbach alpha having a value of more than 0.7. The later section, perceived business performance (PERF), which included financial and market performance, was measured using five factors/items adopted by the researchers (Aktar et al., 2016; Chen & Tsou, 2012; Ghandour, 2015).

4.8. Statistical Tools and Techniques for Data Analysis

The researchers administered the following data analysis or statistical tools and techniques, which were vital in statistically validating the theoretical model. The study followed various stages in data handling, such as data structuring, screening, preparation, and analysis. Data structuring includes variable and value label coding, declaring the type and scale of data. Data screening focused on eliminating unwanted data points and considering that, as per the sample plan, data preparation includes converting into categorical or recategorized data. The following are the types of data analysis tools and techniques administered by the researchers to analyze the data collected with the support of both primary and secondary sources of information. The study used bivariate and multivariate methods to prove the above-said hypothesis; all the variables were examined using descriptive statistics like frequency distribution, mean, and standard deviation. Exploratory Factor Analysis was administered for this research to explore the factors impacting big data analytics capabilities and customers' perceived benefits; exploratory factor analysis was used, keeping eigenvalue> 1, commonalities>.5, Kaiser-Meyer-Olkin Test (KMO) >.5, the extraction method is the Principal Axis Factor (PAF), and oblivion is the rotation method. The researchers also employed the Carl Pearson Co-efficient of Correlation to find the relations among all constructs, which were explored through bivariate correlations and established dimension-wise relations. T-tests and ANOVA were used to prove the significant difference, and t-tests and one-way ANOVA were used across various demographic variables. Measurement error was handled with the help of reliability and validity tests. Regarding reliability, Cronbach alpha was used; face and nomological validity were used to prove the model. The study mainly dealt with psychological constructs; all are latent; all the latent were converted into manifested variables using the item-parcel approach. From e-tailing company representatives ' data, partial least square SEM was used to prove the above theoretical model. The partial least squire-structural equation modeling (PLS-SEM) is an apt procedure for exploring the factors and simultaneously predicting the effect of the outcome variable. Besides this, PLS-SEM can be applied to small samples, even those below 100, and larger samples. Besides this, PLS-SEM does not demand normality of data.

4.9. Software used for Data Analysis

For valuable data analysis, different software was used for various purposes; MS-Excel was used to enter the data, all the variables were positioned in columns, and all the observations were row-wise. SPSS was used extensively for data coding, editing, tabulating, and analysis. To execute the PLS-SEM procedure, R Language and R studio were used to document the coding and seamlessly synch with external software such as MS Word doc and HTML, and R markdown packages were used.

5. Results

The perusal of this most crucial section focuses on the information related to the demographic profile of the subjects, the reliability and validity of the instruments, the tabular presentation of the analyzed results, and the testing of hypotheses.

5.1. Demographic Profile of the Respondents

Table 1: Demographic Profile of the Subjects (N= 70)

S. No.	Demographic Features	Count (70)	Percentage (%)
1.	Number of Companies Responded		
	Company 1	18	25.71
	Company 2	05	7.14
	Company 3	15	21.43
	Company 4	04	5.71
	Company 5	09	12.86
	Company 6	05	7.14
	Company 7	14	20.00
	Total	70	100.00
2.	Designation of Respondents		
	Analytics Manager/ Leaders/ Anchors/ Architechs/ Specialists	06	8.57
	C-Cader Higher Officials (CEO, CTO, COO, CIO, VP, MD, Directors)	03	4.28
	Data/Business Analysts/Data Scientists & Engineers	44	62.86
	Managerial Cader Employees	17	24.89
	Total	70	100.00

S. No.	Demographic Features	Count (70)	Percentage (%)
3.	Experience of Respondents		
	Up to 2 years	04	5.71
	> 2 to 4 years	26	37.14
	> 4 to 6 years	24	34.29
	Above 6 years	16	22.86
	Total	70	100.00

Source: Research findings

In Table 1 above, the researchers did not mention any company name because they maintained a high degree of confidentiality by following the ethical standards of the research. Concerning e-tailing companies, company 1 achieved the highest score of 25.71%, company 3 achieved the next highest score of 21.43, company 7 attained 20%, and company 5 achieved the score of 12.86%. Company 2 and Company 6 scored similarly at 7.14%, while Company 4 reached the lowest 5.71%. Companies 1, 3, and 7 responded more, as these are the leading and large e-tailing firms. Twelve (12) major e-tailing companies were considered for the study by contacting around 350 representatives, of whom 70 respondents from seven e-tailing firms participated in the survey. Regarding the designation of respondents, only six (06), with a percentage of 8.57 analytics specialists, managers, leaders, anchors, and architects, responded as against C-cader employees of just three (03). As expected by the researchers, 62.86 percent of data scientists, business analysts, and data engineers replied promptly against 24.89 managerial cader employees like product managers, analytics managers, marketing and operations managers. Related to the experience of the subjects, 37.14 percent of responses were received from company employees who have experience of above two years and below four years, compared to just 5.71 percent from below two years. 34.29 percent of responses were received from employees with experience above four years and below six years, as opposed to 22.86 percent of responses from above six years.

5.2. Reliability and Validity Tests

The researchers also tested the reliability and validity of the instrument comprehensively item-wise. They found that both Cronbach α and Kaiser-Meyer-Olkin (KMO) values, as mentioned in Table 2 below.

Table 2: Reliability and validity test results (N=70)

Number of Variables	Cronbach α	Kaiser-Meyer-Olkin (KMO)	Bartlett's Test of Sphericity Approx. Chi-Square (df), P-value
05	0.714		
18		0.753	552.353 (153), <.001

Source: Research findings

Reliability analysis was conducted to assess the consistency of the data. Cronbach alpha was computed dimension-wise, viz., customer orientation, supply chain optimization, alignment with products and services, customer traction, and purchase influence. The average Cronbach alpha value for the five dimensions mentioned is 0.714, which is entirely satisfactory. Overall, the KMO and item-wise KMO tests showed the values to be more than 0.5, which ensured a measure of sampling adequacy. Bartlett's test showed a chi-square value of 552.35 and a P value <.001. This confirmed correlation among the items is intact for conducting factor analysis.

5.3. Exploratory Factor Analysis

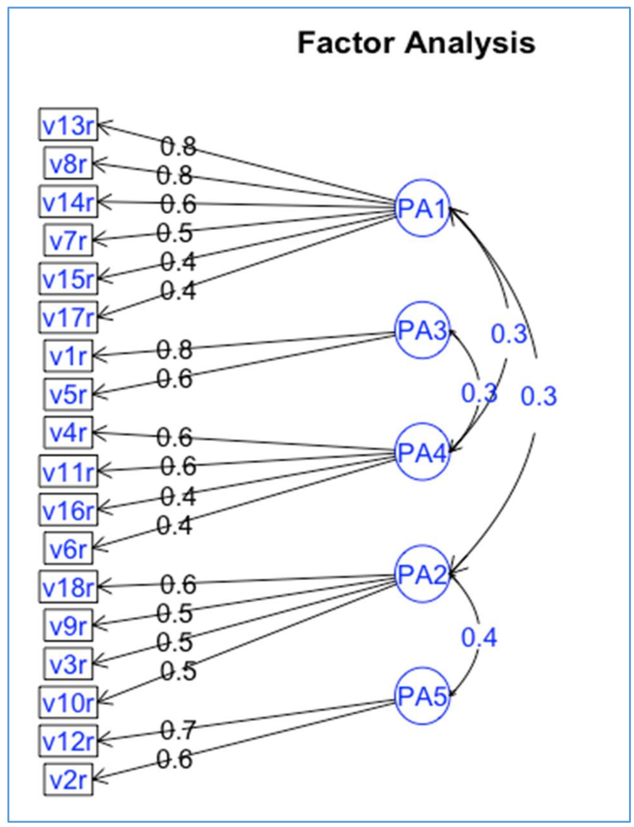

Figure 2: Exploratory factor analysis with rotated factor loading

The factor analysis found that five factors affect data analytics capabilities, namely fac1: Customer Orientation; fac2: Supply Chain Optimization; fac3: Alignment (Products & Services); fac4: Customer traction; fac5: Purchase Influence.

Table 3: Path Coefficient bootstrapped 2000 times

	Original	Mean. Boot	Std. Error	perc. 025	perc. 975
fac1 → BDACap	0.463	0.456	0.046	0.373	0.553
fac2 → BDACap	0.264	0.260	0.031	0.197	0.311
fac3 → BDACap	0.173	0.168	0.021	0.131	0.213
fac4 → BDACap	0.265	0.264	0.034	0.197	0.333
fac5 → BDACap	0.159	0.157	0.029	0.104	0.206
BDACap → Process	0.809	0.817	0.040	0.733	0.882
BDACap → Perf	0.253	0.242	0.156	-0.082	0.529
Process → Perf	0.520	0.554	0.144	0.286	0.844

The path coefficient was tested using the bootstrapped procedure. It was resampled around 2000 times and taken as the average of the resampled, which fell close to the original coefficients of the model. Perc0.025 was the lower limit, and perc0.975 was the upper limit of the confidence interval. When both are of the same sign (either positive or negative), the path is statistically significant at least 5% level. All the paths were statistically significant except BDA Cap → Perf, which showed that BDA Capabilities and Performance might not be significant directly, but if it occurred through BDA Process, it was significant statistically. Hence, the outcome depicted that the BDA Process acted as a complete mediator between the BDA Capabilities and the organization's performance.

5.4. Descriptive Breakdown of the Factor Analysis

Table 4: Descriptive breakdown of the factor analysis

Constructs Name	Cronbach Alpha	Mean	Std	No of items
fac1: Customer Orientation (PA 1)	0.834	4.486	0.400	6
fac2: Supply Chain Optimization (PA 2)	0.676	3.968	0.329	4
fac3: Alignment (Products & Services) (PA 3)	0.715	4.093	0.469	2
fac4: Customer traction (PA 4)	0.703	3.914	0.450	4
fac5: Purchase Influence (PA 5)	0.642	3.629	0.569	2
Big Data Analytics (BDA) Process	0.847	4.103	0.355	9
Financial Performance (Fin Perf)	0.750	4.163	0.416	5
Market Performance (Market Perf)	0.778	3.791	0.439	5

Source: Research findings

As mentioned in Table 4 above, the factors are fac1: Customer Orientation, fac2: Supply Chain Optimization, fac3: Alignment (Products and services), fac4: Customer traction, and fac5: Purchase Influence. Factor analysis shows that five factors direct big data capabilities—nine items from the questionnaire form the data analytics process construct.

5.5. R sqr of the Model

Table 5: R sqr of the model

	Original	Mean. Boot	Std.Error	perc.025	perc.975
Process	0.655	0.670	0.064	0.537	0.777
Perf	0.548	0.594	0.082	0.436	0.754

5.6. Structure Equation Modeling

PLS-SEM Model: Structural equation modeling was used in research as it can test complex theoretical constructs. It has become an essential analytical technique in many disciplines, especially academic research (Hair et al., 2006). The advantage of the structural equation model (SEM) is that it can simultaneously take both measurement and structural model. Besides this, analysis can be made on multiple independent and dependent variables in the form of both latent and manifest. The measurement model was stated as an outer model, and the Structural model was represented as a Structural model per PLS literature. In this study, variance-based SEM, namely PLS-SEM, was made using R software, which provides similar and better results than any other PLS software.

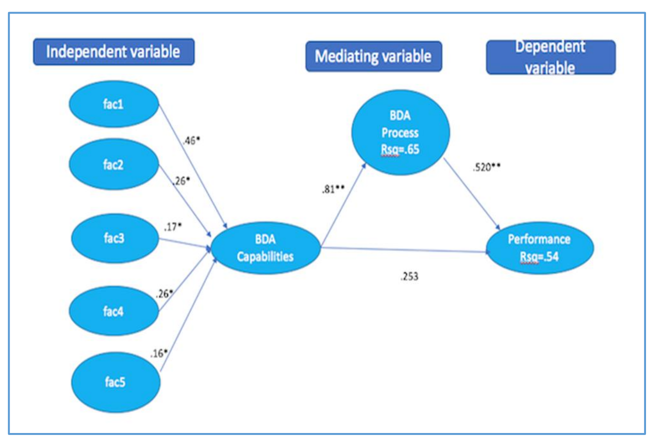

Figure 3: Model on Partial Least Squares-Structural Equation Modeling (PLS-SEM)

Figure 3 emphasizes that all the independent variables impact performance when mediated through processes. The independent variables, as explained, include fac1: Customer Orientation fac2: Supply Chain Optimization fac3: Alignment (Products & Services) fac4: Customer traction fac5: Purchase Influence. The accuracy of the model was assessed through R square. The big data analytics capabilities caused changes in the big data analytics process to the extent of 0.65, and both capabilities and process created changes in performance to the extent of .54 or 54%. From the PLS-SEM Model, it is observed that all the paths are statistically significant except big data analytics capabilities leading to performance. It showed that big data analytics capabilities and performance might not be statistically significant, but if they occurred through the big data analytics process, they were statistically significant. The outcome revealed that the big data analytics process acted like a complete mediator between the big data analytics capabilities and the organization's performance. E-tailing companies must focus on developing big data analytics processes to enhance the firm's performance.

5.7. Hypotheses Testing Results

H1₁. Big data analytics capabilities are related to the big data analytics process – **Accepted**

H2₁. A higher big data analytics process will positively contribute toward higher perceived business performance – **Accepted**

H3₁. The big data analytics process mediates between big data analytics capabilities and perceived business performance – **Accepted**

H4₁. Big data analytics capabilities have a direct effect on perceived business performance – **Rejected**

H5₁. Use of big data analytics positively impacts e-tail business performance - **Accepted**

The PLS-SEM Model shows that the big data analytics capabilities are related to the big data analytics process, which proves hypothesis 1 is valid. The direct, indirect, and total effects of the model and PLS-SEM Model show a direct impact of the big data analytics process on the business organization's performance. The same can be observed in the descriptive analysis in Table 4 with values. The R Sqr table values indicate that the data analytics process (0.847) leads to better-perceived business performance. Based on the above statistical values, hypothesis 2 is accepted. The study highlighted that the big data analytics process strongly mediates big data analytics capabilities and visible business performance, which means hypothesis 3 is also valid. The relationship between data analytics capabilities and perceived business performance is indirect, as the data analytics process completely mediates. Big data analytics capabilities of a company have no direct effect on the business performance, which proves that even hypothesis 4 is not supported. The extensive and effective use of the big data analytics process in any organization significantly impacts e-tailing business performance based on the values highlighted in Table 4 above, which means hypothesis 5 is valid. *P<.05 (at 5% significant level), **P<.01 (at 1% significant level). Before using the construct for model testing, relations among the constructs were explored with the help of the Carl Pearson correlation. Construct relations with performance ranged from 0.24 to 0.87, and all were statistically significant at least 5% level. The financial performance value impacting perceived business performance was 0.87, and the marketing performance value impacting perceived business performance was 0.8 at a 1% significant level where p<.01. The researchers identified a positive impact of using big data analytics on e-tail business performance.

6. Discussion

Based on the findings, the researchers perceived that the big data analytics process is a mediating variable impacting perceived business performance. The process needs re-engineering to make superior decisions, access essential facts and information, turn insights into improved relationships, and know customers better. With the advancement in technology and innovation, e-tailing firms need to develop capabilities to offer personalized user experience online (to address the lack of personal touch), be agile through dynamic pricing, convert online site visitors into buyers, manage inventory levels to avoid excess stocks or stock-outs and cater to needs of people across locations; develop a transparent and responsive supply chain. Expenditure and occupation demographies affect the constructs, perceived benefits, satisfaction, and recommendations. E-tailing firms must carefully work on these demographics to capture new customers and develop appropriate and timely retention techniques. The focus should include e-tailing sites and social media platforms where e-tailers must engage customers online to make a sale and gather valuable comments and feedback that can impact new online users. Multi-language support needs to be extended to online buyers. As a thumb rule, e-tailers need to focus highly on customer satisfaction. This has a more significant impact on the performance of the firm. Successively, the Indian online retail market will attain a different outlook. Creating a sustainable environment mechanism for the futuristic growth of e-tailing in India is necessary. Contribution to the research is mentioned from the perspectives of e-tailing companies. However, the research contributions will focus more on E-Tailing companies and other researchers. Based on an extensive literature review, it was understood that in e-tailing firms, there was little or no understanding of how the role of big data analytics capabilities and big data analytics processes impact a firm's performance. Firstly, the predominant research contribution was explaining the missing link by stating the effect of big data analytics capability on a firm's performance that can be realized through the big data analytics process (strong mediator) from the perspective of e-tailing companies extensively working in India. Secondly, the big data analytics process, which acts as a strong mediating variable, needs re-engineering and innovation to help firms transform capabilities into performance continuously. A comparison with the results obtained by other researchers was impossible as this study was the first of its kind from the Indian context. An extensive academic contribution from scholars like Fozooni et al. (2024) stated that big data analytics and e-commerce technology enable companies to attain a competitive advantage and respond to their customers more efficiently. Another comprehensive research proved similar kinds of impacts and mentioned that big data analytics plays a critical role in revolutionizing e-commerce companies to optimes their business operations, logistics and meeting customer demands (Zhu, 2024)

7. Conclusion

Growth in Internet use, customers' buying ability, and online shopping convenience have increased e-tail business. Big data is vital if e-tail businesses are to stay abreast of consumer demand and preferences. From this research, it is apparent that big data analytics can assist e-tailing companies in enhancing their business performance and customer experience. The use of data analytics has facilitated personalization as well as dynamic pricing. This could help acquire and retain new customers, increase customer satisfaction, and improve brand image and loyalty. In addition to increased sales opportunities, it provides valuable insights regarding process improvement. Big Data Analytics is also helpful for organizations in capitalizing on their data. It emphasizes where improvements need to be made to enhance business Performance, from the e-tailing companies' distribution to customer satisfaction. The research considers only the perceived business performance and not the actual performance permissible in these studies. This research has taken a single point of data, i.e., only one point of time during the research. The results of the studies may not be generalized as the data from third-party players like suppliers and banks in the e-tailing ecosystem is not considered. As this research finds the perceived business performance, there is further scope for conducting the research based on actual performance. Individual e-tailing firms can research cost-benefit analysis to measure the cost of implementing data analytics technology and the benefits reaped over time for calculating return on investment (ROI).

Further, analysis can be done by considering data from multiple points in time. Broader research can be conducted by covering third-party players like suppliers and banks in the e-tailing ecosystem. The scope for future research can address the above areas. The significant limitation of the study is that the research exclusively concentrated on the e-tailing business from the Indian context. The research considers only the perceived business performance and not the actual performance permissible in these studies. This research took a single point of data, i.e., only one point of time during the research. The results of the studies may not be generalized as the data from third-party players like suppliers and banks in the e-tailing ecosystem is not considered.

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