STUDY OF DATA ANALYTICS AFFECTING SME's FOR BUSINESS DECISIONS

A THESIS

SUBMITTED TO
TILAK MAHARASHTRA VIDYAPEETH,PUNE

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UNDER THE BOARD OF MODERN SCIENCES &PROFESSIONAL SKILLS

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CERTIFICATE

This is to certify that the thesis titled, “STUDY OF DATA ANALYTICS AFFECTING SME’s FOR BUSINESS DECISIONS” which is being submitted herewith for the award of degree of philosophy (Ph.D.) in computer science Department of by Tilak Maharashtra Vidyapeeth, Pune is the result of original research work completed by Ms. Asmita R. Namjoshi, under my supervision and guidance. To the best of my knowledge and belief the work incorporated in this thesis has not formed the basis for the awardof any degree or similar title of this or any other University or examining body uponher.

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DECLARATION

I hereby declare that this Ph.D. thesis entitled "STUDY OF DATA ANALYTICS AFFECTING SME's FOR BUSINESS DECISIONS", completed and written by me has not previously formed the basis for the award of any degree or other similar title upon me of this or any other Vidyapeeth or examining body.

Place: Pune　　　　Ms. Asmita R. Namjoshi

Date:　　　　Research Scholar

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List of Abbreviations

Abbreviation	Explanation
ABDA	Application of Big Data Analytics
BA	Business Analytics
BA	Business Analytics
BD	Business Data
BDA	Business Data Analytics
BDN	Benefit Dependency Network
BI	Business Intelligence
CDNs	Content Delivery Networks
CDO	Chief Data Officer
CEO	Chief Executive Officer
CIO	Chief Information Officer
CMIO	Chief Medical Information Officer
CPO	Chief Privacy Officer
CRISP-DM	Cross Industry Standard Process for Data Mining
DA	Data Analytics
DDC	Data Driven Culture
DIC	District Industry Centre
DIKW	Data-Information-Knowledge-Wisdom
ER	Entity Relation
ES	Environmental Scanning
fsQCA	fuzzy-set Qualitative Comparative Analysis
ICSD	Composite Sustainable Development Index

IT	Information Technology
KDD	Knowledge Discovery in Databases
KM	Knowledge Management
KMP	Knowledge Management Practises
KPI	Key Performance Indicator
MSMEs	Micro, Small, and Medium-Size Enterprises
NPM	New Product Meaningfulness
OM	Operations Management
OP	Organisational Performance
PLS-SEM	Partial Least Squares Structural Equation Modelling
R&D	Research And Development
RdM	Redistributed Manufacturing
ROI	Return On Investment
RQ	Research Question
SCM	Supply Chain Management
SEMMA	Sample, Explore, Modify, Model, and Assess
SIGDSS	Special Interest Group on Decision Support Systems
SMA	Sustainability Management Accounting
SMEs	Small and Medium Enterprises
SOHO	Small Office-Home Office
SSE	Small Scale Enterprise
TQM	Total Quality Management
US	United States

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Chapter – 1: Introduction

1.1 Data Analytics

Data: Data is a big collection of writings, photos, sounds, videos, and other types of information. It has no meaning unless you add information to it. When we combine data, it becomes more meaningful and transforms into knowledge.

Analytics: Analytics is the transformation of raw data into actionable strategic information in order to gain insight into corporate processes and, as a result, drive decision-making to help firms run more efficiently.[1]

The branch of Data Science that deals with data analytics is known as data science. Data science is an interdisciplinary topic that focuses on extracting useful information from enormous amounts of unstructured and structured data. The field is largely concerned with discovering answers to questions we don't yet understand. Experts in data science employ a variety of methodologies to find answers, including computer science, predictive analytics, statistics, and machine learning to sift through enormous information and find solutions to problems that haven't been considered before.

The processing and statistical analysis of existing datasets is the subject of data analytics. Analysts focus on developing ways for capturing, processing, and organising data in order to unearth actionable insights for current issues, as well as determining the best manner to communicate this information. Simply said, data and analytics is concerned with finding solutions to challenges for which we are unsure of the answers. It's also predicated on delivering results that can result in quick benefits.

[1]**Subrata Das (2013).** Computational Business Analytics. CRC Press Chapman & Hall.

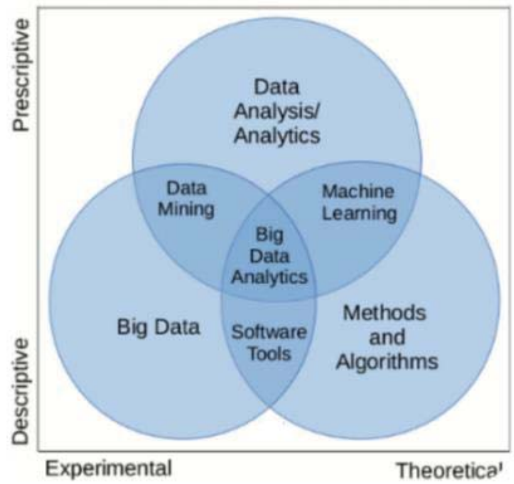

Figure 1: The Fields of Data Science

1.2 Difference between Data Science and Data Analysis

Data Science and Data Analytics both deal with Big Data, but in different ways. Data Science is a broad term that incorporates both data analytics and data science. Mathematics, Statistics, Computer Science, Information Science, Machine Learning, and Artificial Intelligence are all included in Data Science.

Data mining, data inference, predictive modelling, and machine learning algorithm development are all used to discover patterns from large datasets and turn them into meaningful business strategies. Data analytics, on the other hand, is mostly concerned with Statistics, Mathematics, and Statistical Analysis. Data Analytics is aimed to reveal the particular of extracted insights, whereas Data Science focuses on uncovering significant correlations between vast datasets. To put it another way, Data Analytics is a subset of Data Science that focuses on more detailed solutions to the issues that Data Science raises.

Data Science aims to find fresh and interesting issues that might help businesses innovate. Data analysis, on the other hand, tries to uncover answers to these questions and decide how they might be implemented within a company to encourage data-driven innovation.

Difference between Data Analytics and Data Analysis:

Although the terms data analysis and data analytics are sometimes used interchangeably, they have slightly different meanings. Essentially, the main distinction between analytics and analysis is one of scale, as data analytics is a larger word that includes data analysis. The process of evaluating, changing, and organising a data collection in specified ways in order to investigate its constituent elements and extract relevant information is known as data analysis. Data analytics is a broad science or field that incorporates all aspects of data management. This encompasses data gathering, organisation, storage, and all instruments and procedures employed, in addition to analysis.

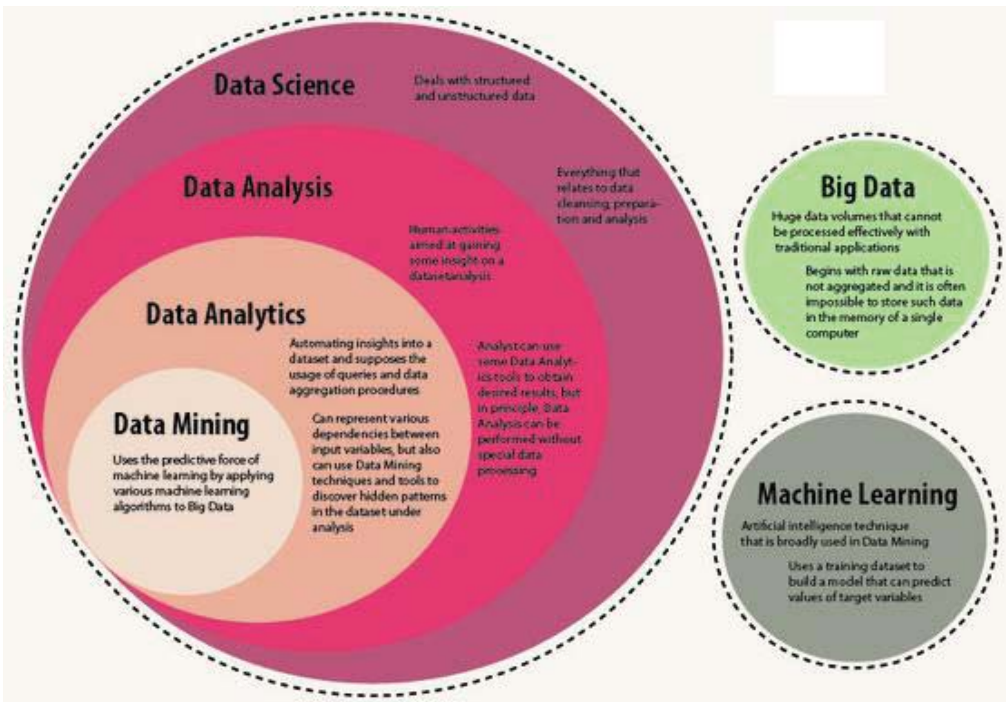

Figure 2: Difference Between Data Analytics, Data Analysis, Data Mining, Data Science, Machine Learning and Big Data

1.3 Data Analysis Process

Data analysis is the process of looking at, cleaning, transforming, and training data with the goal of uncovering usable information, making recommendations, and assisting in decision-making. Data analytics combines data, machine learning, statistical analysis, and computer-based models to help people gain a better understanding of their data and make better decisions. The process of transforming data into actions through analysis and insight in the context of organisational decision-making and problem-solving is well-defined as analytics.

For analysing massive and complicated data sets, data analytics employs basic scientific concepts. It's an inquiry, purification, transformation, and data modelling procedure with the goal of identifying essential data, recommending conclusions, and supporting decision-making processes. It encompasses a variety of methodologies within a category of denominations in science, diverse business, social sciences, and other research fields, and it has multiple viewpoints and perspectives. Analytics is the study of analysing raw data in order to derive usable knowledge (pattern).[2] Data collection, pre-processing, transformation, modelling, and interpretation are all part of this process, as shown in Fig. 1.3.

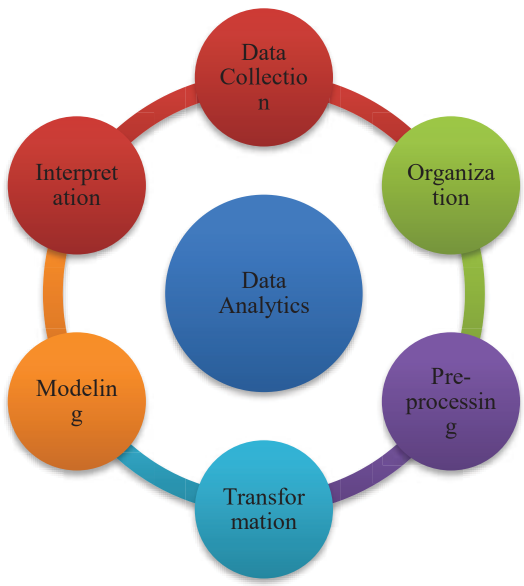

Figure 3: Data Analytics Process

1.3.1 Data Processing

Data processing is the process of transforming a large, noisy, incomplete, and inconsistent set of data into high-quality, productive data in a variety of ways, including fit for analysis, aggregation with other relevant data, supplement or subordination for alternative data, and so on. It's also known as data conversion or transformation into a usable and useful format.

1.4 Knowledge Discovery in Database

The process of discovering usable knowledge from a set of data is known as knowledge discovery in databases (KDD). This extensively used data mining technique entails data preparation and selection, data purification, adding prior knowledge into data sets, and accurately interpreting the observed results.

The term KDD stands for Knowledge Discovery in Databases. It refers to the broad process of uncovering knowledge from data, with a focus on high-level applications of specialised Data Mining techniques. Artificial intelligence, machine learning, pattern recognition, databases, statistics, knowledge acquisition for expert systems, and data visualisation are all sectors that are interested in it.

The primary goal of the KDD procedure is to extract information from data in huge databases. It accomplishes this by employing Data Mining algorithms to determine what constitutes knowledge. Knowledge Discovery in Databases (KDD) is defined as a systematic, exploratory investigation and modelling of large data sets. KDD is a systematic method for identifying valid, useful, and intelligible patterns in large, complicated data sets. The inference of algorithms that explore the data, construct the model, and identify previously unknown patterns is at the heart of the KDD approach. The model is used to extract knowledge from data, analyse it, and make predictions about it.

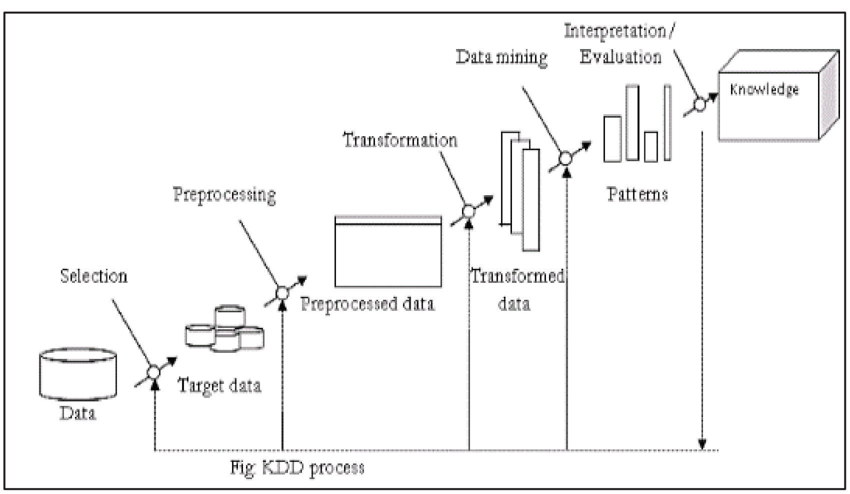

Figure 4: KDD Process[2]

1. Building up an understanding of the application domain

This is the first step in the process. It sets the stage for figuring out what to do with various decisions like transformation, algorithms, and representation, among others. Individuals in charge of a KDD project must comprehend and characterise the end-goals user's as well as the environment in which the knowledge discovery process will take place (involves relevant prior knowledge).

2. Choosing and creating a data set on which discovery will be performed

The data that will be used for the knowledge discovery process should be determined once the objectives have been identified. The aspects that will be evaluated for the process include identifying what data is available, acquiring important data, and then integrating all of the data for knowledge discovery into one set. Data Mining learns and finds from the available data, hence this process is crucial. This is the evidence on which the models are based. The more attributes analysed, the more likely the study will be ineffective in this regard if certain essential attributes are absent.

On the other hand, it is costly to organise, gather, and manage complex data repositories, and there is a deal in place that allows for the greatest understanding of the phenomena. This configuration refers to a part of the KDD that is interactive and iterative in nature. This starts with the best data sets available and then expands and monitors the impact in terms of knowledge discovery and modelling.

3. Pre-processing and cleansing

Data dependability is increased in this step. It includes data cleaning, such as dealing with missing values and removing noise or outliers. In this case, it might apply complicated statistical techniques or a Data Mining programme. For example, if one suspects that a particular characteristic is unreliable or has a lot of missing data, that attribute could become the goal of the Data Mining supervised method. Following the creation of a prediction model for these properties, missing data can be forecasted. The extent to which one pays attention to this level is determined by a variety of circumstances. Regardless, examining the features is important and frequently illuminating to company data frameworks on its own.

4. Data Transformation

This stage involves preparing and developing appropriate data for Data Mining. Dimension reduction (for example, feature selection and extraction, and record sampling) are used here, as well as attribute transformation (for example, discretization of numerical attributes and functional transformation). This stage is often project-specific and can be critical to the success of the entire KDD project. In medical examinations, for example, the quotient of qualities, rather than each one individually, may be the most important component. We may need to consider influences beyond our control, as well as efforts and temporary challenges, in business.

Examining the effects of advertisement build up, for example. However, if we don't start with the appropriate transformation, we might get a wonderful result that tells us about the transformation we'll need in the following iteration. As a result, the KDD process feeds back on itself, prompting an understanding of the essential transformation.

5. Prediction and description

We're now ready to choose the type of Data Mining to apply, such as classification, regression, clustering, and so on. This is primarily dependent on the KDD objectives, as well as the preceding steps. Data Mining has two major goals: the first is to make a forecast, and the second is to make a description. Predictive Data Mining is commonly referred to as supervised Data Mining, whereas descriptive Data Mining includes the unsupervised and visualisation components of Data Mining.

Inductive learning is used in most Data Mining approaches, where a model is generated explicitly or implicitly by generalising from a sufficient number of preparatory models. The inductive approach is based on the idea that the created model is applicable to future occurrences. The method additionally considers the level of meta-learning for the specific collection of data available.

6. Selecting the Data Mining algorithm

Now that we've figured out the technique, it's time to figure out the tactics. This stage entails deciding on a technique to utilise while searching for patterns containing numerous inducers. When it comes to precision vs. understanding ability, for example, neural networks excel at the former whereas decision trees excel at the latter. There are numerous approaches to achieving meta-learning success for each system. Meta-learning is concerned with determining what causes a Data Mining algorithm to be successful or unsuccessful in a given situation. As a result, this methodology tries to figure out what kind of situation a Data Mining algorithm is most suited for. Each algorithm has its own set of parameters and leaning tactics, such as tenfold cross-validation or a separate training and testing division.

7. Utilizing the Data Mining algorithm

At long last, the Data Mining method has been implemented. We may need to use the method numerous times at this point to get a satisfactory result. By adjusting the algorithms, for example, you can modify parameters like the minimum number of instances in a single decision tree leaf.

8. Evaluation

In this phase, we evaluate and analyse the mined patterns, rules, and reliability in relation to the first-step goal. In this section, we look at the pre-processing procedures and how they affect the Data Mining method outputs. Include a feature in step 4, for example, and then repeat the process. This step focuses on the induced model's readability and utility. The recognised knowledge is also documented in this phase for future use. The utilisation, as well as overall feedback and discovery outcomes obtained by Data Mining, is the final phase.

9. Using the discovered knowledge

We are now ready to incorporate the knowledge into a different framework for further action. Knowledge becomes useful when it allows us to make changes to the system and track the results. The success of this stage determines the overall effectiveness of the KDD process. This phase presents a number of obstacles, including the loss of the "laboratory settings" in which we previously operated. For instance, information was obtained from a static portrayal, which is usually a set of data, but the data has now become dynamic. Certain quantities may become unavailable as a result of changes to data structures, and the data domain may be altered, such as an attribute with a value that was not expected earlier.

1.5 Types of Data Analytics

The field of data analytics is vast. Data analytics can be classified into four categories: descriptive, diagnostic, predictive, and prescriptive. Each category has a distinct purpose and function in the data analysis process. These are also the most common business data analytics applications.

- Descriptive analytics aids in the investigation of events. To describe outcomes to stakeholders, these strategies synthesise big datasets. These tactics can help track successes and failures by establishing key performance indicators (KPIs). In many businesses, metrics like return on investment (ROI) are used. To track success in certain industries, specialised metrics are devised. This procedure necessitates the gathering of relevant data, data processing, data analysis, and data visualisation. This procedure provides crucial information about previous performance.
- Diagnostic analytics can assist you figure out why something happened. These strategies are used in conjunction with more basic descriptive analytics. They take the results of descriptive analytics and delve further to discover the root of the problem. The performance indicators are looked at further to see why they have improved or deteriorated. This usually happens in three stages:
- Look for discrepancies in the data. These could be unanticipated changes in a statistic or a market.
- Information about these anomalies is gathered.
- Relationships and trends that explain these abnormalities are discovered using statistical approaches.
- Predictive analytics can assist you figure out what will happen in the future. These methods make use of historical data to uncover patterns and decide if they are likely to repeat again. Predictive analytical tools use a number of statistical and machine learning approaches, such as neural networks, decision trees, and regression, to provide significant insight into what might happen in the future.
- Prescriptive analytics assists in determining what should be done. Data-driven decisions can be made utilising predictive analytics insights. In the face of uncertainty, this enables firms to make educated judgments. Machine learning strategies are used in predictive

analytics techniques to detect trends in massive datasets. The chance of various outcomes can be estimated by analysing past decisions and events.

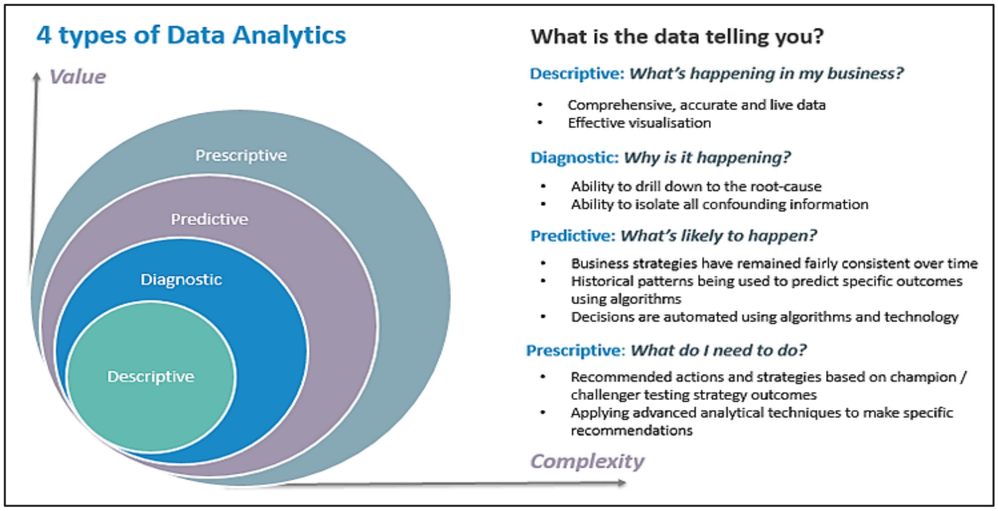

Figure 5: Types of Data Analytics

These forms of data analytics give firms the information they need to make informed decisions. They provide a well-rounded picture of a company's demands and potential when used together.

1.5.1 Areas Using Data Analytics

1. **Banking and Securities**: To reduce fraudulent transactions by using network activity monitors and natural language processors to monitor financial markets. By monitoring the stock market, exchange commissions or trading commissions use big data analytics to ensure that no illicit trading occurs.
2. **Communications and Media**: For simultaneous real-time reporting of global events on multiple platforms (mobile, web, and television). Big data is being used by the music industry, a section of the media, to keep track of the latest trends, which are then employed by auto tuning software's to create catchy compositions.
3. **Sports:** Understanding viewership patterns for various events in certain regions, as well as analysing the performance of individual players and teams. Big data analytics is used extensively at sporting events such as the Cricket World Cup, FIFA World Cup, and Wimbledon.

4. **Healthcare**: To gather public health data in order to respond more quickly to individual health issues and to track the global spread of novel viral strains like Ebola. Different countries' health ministry’s use big data analytic techniques to make effective use of data obtained through censuses and surveys.
5. **Education**: To update and revise required material in a range of domains that are rapidly evolving. Universities all over the world are utilising it to track and monitor the performance of their students and faculties, as well as map student interest in various disciplines through attendance.
6. **Manufacturing**: To improve supply chain management by utilising big data to boost productivity. These analytical techniques are used by manufacturing companies to guarantee that they are allocating production resources in the most efficient way possible.
7. **Insurance**: Predictive analytics is used for everything from inventing new goods to resolving claims. Insurance companies utilise big data analytics to keep track of which policy schemes are most popular and generate the most income.
8. **Consumer Trade**: To forecast and manage inventory and staffing needs. It is being used by consumer trading companies to expand their business by distributing loyalty cards and keeping track of them.
9. **Transportation**: Better route planning, traffic monitoring and management, and logistics are all advantages. Governments primarily use this to avoid traffic congestion in a single location.
10. **Energy**: Smart metres are being introduced to help users manage their energy usage and decrease electrical leakages. Big data analysis is being used by load dispatch centres to monitor load patterns and discover variances in energy consumption trends based on various characteristics, as well as to implement daylight savings.

1.6 Information Hierarchy

The Data-Information-Knowledge-Wisdom (DIKW) hierarchy, often known as the pyramid, connects data, information, knowledge, and wisdom in four layers. Data is the most fundamental level; information provides context; knowledge clarifies how to utilise it; and wisdom clarifies when and why to use it. In the DIKW hierarchy, data is only a basic fact and raw material that can only be helpful if it evolves into information, knowledge, and wisdom.

To make the preceding two tiers of data and information useful, we can utilise a variety of approaches and technologies such as data mining, text mining, web mining, and data bases, data warehouses, and management information systems.[3] We should employ KDD, knowledge engineering and management, and intelligent knowledge to advance to the third level of knowledge. Intelligent knowledge management, when combined with large-scale databases, allows for the creation of "special" knowledge, dubbed intelligent knowledge, based on hidden patterns discovered by data mining. The intelligent knowledge management process is offered as a novel idea based on original data, rough information, intelligent knowledge, and actionable knowledge.[4]

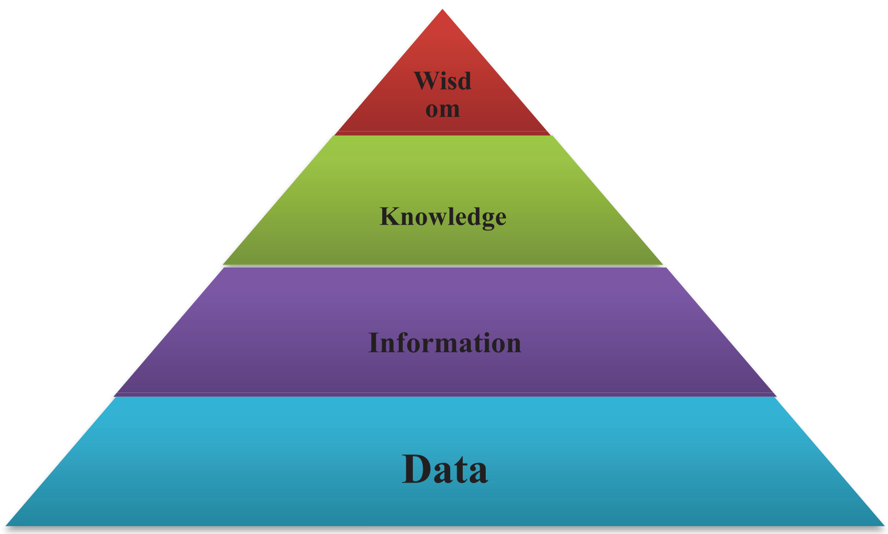

Figure 6: Information Hierarchy

Data: Data is a collection of unprocessed facts and figures. The mere existence of data is inconsequential in and of itself. The information may or may not be usable.

Information: We acquire information when this data is analysed to determine the relevant data. Information is nothing more than facts that have been digested. The majority of this processing is done by linking data pieces with the goal of determining relevance.

Knowledge: The general awareness or possession of information, facts, concepts, or principles is known as knowledge. Knowledge can be derived from underlying data.

Wisdom: Wisdom is the accumulation of knowledge that enables you to adapt concepts from one domain to new situations or challenges. With vision foresight and the ability to look beyond the horizon, wisdom is the ultimate level of abstraction. In each given scenario, wisdom is defined as the ability to behave critically or practically. It is based on an individual's ethical judgement in relation to their belief system.[5]

The following techniques can be used to improve the effectiveness of data analytics tools for business:

- Machine learning
- Regression analysis
- Sentiment analysis
- Social network analysis
- Association rule learning
- Classification tree analysis
- Genetic algorithms

1.7 Influence of Data Analytics on Industry

Data analytics is a technology-enabled method for extracting richer, deeper, and more accurate insights from large amounts of data and, as a result, establishing a competitive edge through quick and accurate judgments. Organizations can make time-sensitive choices faster than ever before, monitor developing trends, course-correct quickly, and seize new business possibilities by analysing a continual supply of real-time data. It has been discovered that numerous businesses are consuming a big number of critical information that might be beneficial in other domains such as object activity monitoring, sensor deployment, data tracking, and so on.

The techniques used to analyse data in order to improve efficiency and business gain are referred to as data analytics. To analyse distinct behavioural patterns, data is extracted from multiple sources, cleaned, and categorised. Depending on the business or individual, different strategies and instruments are used.

Data analytics is becoming more specialised, and its capacity to influence practically every industry gives it a deterministic presence that portrays it as an implement-and-reap beneficial option for businesses. Many businesses, even SMEs, struggle to successfully deploy technological and organisational frameworks that enable them to capture a significant portion of the potential that data, both little and large, might possess. The initial applications of gathering a huge variety and volume of knowledge were largely within major organisations, and were used for fraud detection and retail coupon systems.

The study is motivated by the fact that SMEs, rather than big corporations, have a limited understanding of the potential of Data Analytics. Larger firms have largely started programmes to complement their analytical capabilities, but as technologies advance and more companies embrace frameworks for handling data and learn how to organise under this new framework, SMEs may have an easier time reaping some of the benefits. SMEs today face less of a constraint on upfront investment, thanks to cheaper and more immediately accessible servers and data centres provided by cloud vendors. Instead, the obstacles are organisational and strategic in character.

Although the appropriate technology must still be picked, with well-supported and documented open-source data systems now available, it's increasingly becoming a matter of selecting the correct solution, one that is scalable and meets the specific needs of a small business.

1.7.1 Benefits of Data Analytics for Business

- **Enables management to make better decisions:** Big data analytics serves as a trusted advisor for strategic planning in an organisation. It assists your management and employees in improving their analytical abilities and, as a result, their general decision-making abilities. Upper management can then set new targets by measuring, recording, and tracking performance metrics.
- **Aids in identifying trends to stay competitive:** As previously stated in this piece, one of data analytics' primary goals is to find patterns in massive data sets. This is especially helpful for spotting new and emerging market trends. These patterns, once detected, could be the key to achieving a competitive edge through the introduction of new products and services.
- **Improves staff productivity and dedication to core activities and issues:** Data science can make employees more productive at their jobs by making them aware of the benefits of using the organization's analytics product. These personnel will be able to drive more action toward fundamental tasks and challenges at every level if they have a better understanding of the company's aims. As a result, your company's total operating efficiency

will improve.

- **Identifies and acts on opportunities:** Data science is all about looking for ways to improve the way things work in organisations. Data scientists can bring new methods of doing things by identifying inconsistencies in organisational procedures and existing analytical systems. This, in turn, can spur innovation and allow for the development of new products, resulting in more economic opportunities for your organisation.
- **Encourages low-risk data-driven action plans:** Big data analytics has enabled small and large enterprises to act on quantifiable, data-driven facts. Such a technique can save a company time and money by avoiding superfluous work, as well as foreshadowing dangers.
- **Validates decisions:** Analytics not only allows your organisation to make data-driven decisions, but it also allows you to test those judgments by introducing variable factors to see if they are flexible and scalable. You may make positive improvements to your organization's structure and operation by utilising data science and big data solutions.
- **Assists in target audience selection:** One of the primary value propositions of big data analytics is the ability to shape customer data in order to have a better understanding of consumer preferences and expectations. A more in-depth study of consumer data can assist businesses in precisely identifying and targeting their target audiences with custom-made products and services.
- **Facilitates intelligent talent recruitment:** Human resource departments are continuously on the lookout for employees who meet the company's requirements. Big data has made their job easier by combining social media, corporate profiles, and job search databases to provide comprehensive data profiles on individuals. Your HR department can now process CVs considerably more rapidly and attract the best individuals without sacrificing quality.

1.8 Tools of Data Analytics

As the market's demand for Data Analytics grows, a slew of new tools with a variety of features have arisen to meet it. The following are the top data analytics tools, which are either open-source or user-friendly.

- **R programming** - R programming is the most widely used analytics tool for statistics and data modelling. R is a programming language that can be compiled and run on a variety of systems, including UNIX, Windows, and Mac OS. It also includes tools for automatically installing all packages based on the needs of the user.

- **Python** - Python is a free, object-oriented programming language that is simple to understand, create, and maintain. Scikit-learn, Tensor Flow, Matplotlib, Pandas, Keras, and other machine learning and visualisation packages are available. It can also be built on any platform, such as SQL server, MongoDB, or JSON.
- **Tableau Public** – This is a free programme that can connect to any data source, including Excel, corporate data warehouses, and so on. It then provides visualisations, maps, dashboards, and other web-based applications with real-time changes.
- **QlikView** – This tool allows users to perform in-memory data processing and receive results quickly. It also provides data association and visualisation, with data compressed to less than 10% of its original size.
- **SAS** – An easy-to-use programming language and environment for data processing and analytics, SAS can analyse data from a variety of sources.
- **Microsoft Excel** – One of the most extensively used data analytics tools is Microsoft Excel. This tool evaluates the jobs that summarise the data with a preview of pivot tables and is primarily used for clients' internal data.
- **Rapid Miner** – A robust, integrated platform that can work with a variety of data sources, including Access, Excel, Microsoft SQL, Teradata, Oracle, and Sybase. Predictive analytics, such as data mining, text analytics, and machine learning, are commonly employed with this technology.
- **KNIME** – The Konstanz Information Miner (KNIME) is an open-source data analytics tool for analysing and modelling data. Through its modular data pipeline architecture, KNIME provides a platform for reporting and integration with the benefit of visual programming.
- **Open Refine** – This data cleaning software, often known as Google Refine, will assist you in cleaning up data for analysis. It's used to clean up messed-up data, convert it, and parse data from websites.
- **Apache Spark** – This technology, which is one of the largest large-scale data processing engines, processes Hadoop cluster applications 100 times quicker in memory and 10 times faster on storage. This programme is also used to create data pipelines and machine learning models.

1.9 Decision Making

"Decision-making involves the selection of a course of action from among two or more possible alternatives in order to arrive at a solution for a given problem". [3]

-By Trewatha & Newport

Modern management relies heavily on decision-making. Essentially, the primary job of management is to make rational or sound decisions. Every manager makes hundreds of decisions, either subconsciously or consciously, making it a critical component of the manager's position. Decisions are crucial because they govern both organisational and managerial activity. A decision is a course of action chosen from a collection of options with the intent of achieving organisational or managerial objectives or goals.

The decision-making process is an ongoing and essential part of running any business or organisation. Decisions are taken to keep all business activities and organisational functions running smoothly. To guarantee that organisational or commercial goals are met, decisions are taken at all levels of management. Furthermore, decisions are one of the key functional values that every organisation adopts and implements in order to achieve optimal growth and drivability in terms of services and or products provided.

1.9.1 Types of Decision

1. Tactical and Strategic Decisions

Tactical decisions are ones that a management makes repeatedly while conforming to a set of rules, policies, and procedures. They're repetitious in nature and have something to do with overall functioning. Lower levels of the organisation are frequently given authority to make tactical decisions. Strategic judgments, on the other hand, are more difficult to make. They have an impact on the company's future and engage the entire team. Strategic decisions include decisions on the business's goal, capital expenditures, plant layout, production, and so on.

2. Programmed and Non-Programmed Decisions

These are decisions that are made on a regular basis. The programmed decisions are essentially routine in nature, with systematic procedures in place to ensure that the problem is not treated as a one-off each time it arises. Non-programmed judgments are complicated and require special attention. If all of the professors in a department stop teaching, the situation cannot be handled by following set procedural rules. It becomes an issue that necessitates a thorough investigation into the origins of the situation, and after examining all variables, a solution can be found through the problem-solving process.

3. Basic and Routine Decisions

Prof. Katona divides decisions into two categories: basic and routine. Basic judgments are ones that demand a great lot of thought and are extremely important. These choices necessitate the development of new norms through a purposeful thought-provoking approach. Plant location, product diversity, and distribution channel selection are all examples of basic decisions. Routine decisions are repetitious in nature and so need little thought. It can be seen that basic decisions are tied to strategic aspects of an organisation, whereas routine decisions are related to tactical aspects.

4. Organizational and Personal Decisions

The decisions that an executive makes in his official position and that can be delegated to others are known as organisational decisions. Personal decisions, on the other hand, are those made by an executive in his individual capacity rather than as a member of an organisation.

5. Off-the-Cuff and Planned Decisions

Decisions made on the spur of the moment are referred to as "shooting from the hip." These judgments are simple to make and can be tailored to the company's objectives. Planned decisions, on the other hand, are tied to the organization's goals. They are founded on facts and use the scientific method to solve problems.

6. Policy and Operating Decisions

Top management makes policy decisions, which have a fundamental impact on the entire company. Lower management makes operating decisions in order to carry out policy decisions. Operating decisions primarily affect the decision maker's own work and behaviour, whereas policy decisions have an impact on subordinates' work and behaviour patterns.

7. Policy, Administrative and Executive Decisions

Decisions in business organisations are characterised as follows by Ernest Dale.

Policy decisions, administrative decisions, and executive decisions are the three types of decisions.

Top management or administration of an organisation makes policy decisions. They are concerned with important concerns and policies such as the financial structure, marketing policies, and the organization's structure outline.

Middle management makes administrative decisions, which are less essential than policy decisions. According to Ernest Dale, the advertising budget size is a policy decision, while media selection is an example of an administrative decision.

Executive decisions are taken at the point where the task is being completed. Identifying the differences between these three sorts of judgments "Policy decisions set forth goals and general courses of action". Dale writes, "Administrative decisions establish the means to be used, and executive decisions are made on a daily basis as specific cases arise".

1.10 Levels of Management

Figure 7: Levels of Management-Source –

(https://www.managementstudyguide.com/management_levels.htm)

1. Top-level Management

Top-level management is made up of an organization's most senior executives and decision-makers. Every member of top management is accountable for the company's direction and progress. A company's success and destiny are largely determined by its top-level management.

This category includes all C-level executives as well as a few other titles. Some of the highest-level classifications are –

- Chief Executive Officer
- Chief Marketing Officer
- Chief Sales Officer
- Chief Technology Officer
- President
- Managing Director
- Vice-president
- Chief Operating Officer
- And a few other designations

The correct group of people in charge of an organisation can make or break it. We'd want to also educate you about the roles that these executives play inside an organisation —

- Top-level management is in charge of planning and formulating company plans. They help every employee and client grasp the principles of any organisation by forming the company's vision and goal.
- They define middle-level management's functions and responsibilities. Employees will be given tasks and targets to complete.
- The company's policy is drafted by top management.
- They are in charge of the company's finances and commitments. In sum, they are exclusively responsible for the Organization's survival and expansion.

2. Middle-level Management

The chiefs of numerous departments in a company make up middle-level management. These executives are in charge of keeping top-level management and lower-level management in touch. They are in charge of the majority of the organization's executions and micromanagement. The following are some examples of typical designation titles for mid-level management executives:

- Marketing Manager
- Purchase Head

- Sales Manager
- Operations Manager
- Branch Manager
- Finance Manager
- And similar other designations

Middle-level executives are in charge of a basic range of functions and responsibilities. The most important of these are:

Disseminate top-level management's policies and mission statements. They are in charge of handling all correspondence and ensuring that the office is kept in a healthy working environment.

- Micro-manage every member of the lower-level management team's tasks. They are in charge of overseeing all team coordination.
- They are in charge of the work of lower-level executives. A critical responsibility is to motivate and encourage staff to work productively.
- All recruitment and allocations within a team are handled by middle-level management. They hire personnel and manage firm resources to make the most of them.

3. Operational/Lower-Level Management

The coordination between the operational workforce and middle-level management is the responsibility of operational level management. They supervise teams and micromanage specific duties to operative personnel. Operational management has little decision-making authority and is primarily responsible for carrying out the commands of middle-level management. Company resources for optimal use is one of the traditional designations of operational level management executives.

- Supervisor
- Foreman
- Clerk
- Junior Managers

- Inspectors
- Sub-department executives

Their job, like that of all other levels of management, is vital to an organization's success. The distinction is that they do not make crucial decisions and rely on middle-level management for efficiency and performance. The following are some of the critical roles played by operational level management:

- Communication of the issues and frustrations of operative personnel is the most important task of operational level management.
- They are in charge of training and monitoring the workers' progress.
- They are in charge of maintaining safe working conditions for employees and increasing job efficiency. Workers at the operational level ensure that the company's operations requirements are followed.
- These executives are in charge of managing corporate resources and ensuring that they are used to their full potential.
- They assist middle-level management in evaluating employee performance and all other aspects of the company's human resources department.

1.11 Small and Medium Enterprises

"Small and mid-size firms (SMEs) are businesses that maintain revenues, assets or a variety of employees below a certain threshold," according to DANIEL LIBERTO[3]. What comprises a small and medium-sized firm (SME) is defined differently in each country."

Small and medium enterprises (SMEs) have long been a mainstay of the global enterprise environment. Growth that has a demonstrated benefit for poverty reduction, in particular, places a priority on integrating small and medium businesses into the economic growth process in a productive and profitable way. The overarching objective must be to establish a market-based economic system with a level playing field for all businesses, in which SMEs can aspire to development and wealth creation prospects commensurate with their own resources, diligence, creativity, and management dedication.

Governments, in particular, tend to think of SMEs as a homogeneous group. This, however, obscures the vast disparities in size, structure, and purpose that exist within the industry.

It is difficult to define the SME sector, and particularly small enterprises, because there are disparities in what is appropriate or proper to classify as "small" in various industries. The number of employees, turnover, and balance sheet total are the major characteristics used to define the SMEs sector.[4] SMEs are defined as businesses with fewer than 500 employees in the United States (US).

The following definitions will be used to classify small and medium Enterprises:

a. Businesses engaged in the manufacture, production, processing, or preservation of commodities, as defined by the Indian government:

- **Small enterprise:** A small business is defined as one with a plant and machinery investment of more than Rs. 25 lakhs, but less than Rs. 5 crore[4].
- **Medium-sized enterprise:** A medium-sized business is one with a plant and machinery investment of more than Rs.5 crores but less than Rs.10 crore[4].

b. Non-manufacturing activities (such as trading or other services)

- **Small business:** A small business is defined as one with an investment in equipment of more than Rs.10 lakhs, but less than Rs.2 crores.[3]
- **Medium-sized business:** A medium-sized business is one with an equipment investment of more than Rs. 2 crores, but less than Rs. 5 crore[4].

Certain size requirements must be met, and the industry in which the company works is generally taken into account as well. The criteria for determining a SME differ by country and industry.

1.12 Data Analytics and Decision Making

In today's society, decision-making is an essential component of organisations. In essence, business decisions influence whether a company will succeed or fail in a given setting. Due to the different influences at play, the decision-making process remains complicated. The business decision-making process is influenced by a variety of factors. Furthermore, human beings are clever beings. As a result, when confronted with various options in the workplace, managers become indecisive. Permissiveness in making right decisions raises the likelihood of corporate failure. To ensure that the organisations benefit from all situations in the business environment, decisions must be correct and quick.

Data analytics facilitates the analysis and interpretation of data into useful information for enterprises. Since the 1950s, data analytics has improved dramatically, and firms now have access to more powerful and speedier technology. The process of reviewing, cleansing, manipulating, and modelling data with the objective of identifying relevant information, informing conclusions, and assisting decisions is known as data analytics. It's a process of studying data sets in order to derive conclusions about the information they contain, with the use of specialised systems and software in recent years. Data analytics is a term that relates to qualitative and quantitative approaches and processes that are used to increase productivity and profit.

Data is extracted and categorised here in order to identify and analyse behavioural trends. In sectors, data analytics technology and methodologies are widely used to help companies make better business decisions. These methods differ depending on the needs of the company.

Data analytics monitors and records events from a variety of sources, including corporate transactions, social media, and machine-to-machine or sensor data. This generates a tremendous amount of data. It also deals with high-speed data streams in a timely manner. It processes and analyses streamed data to deliver near-real-time results. It is capable of handling a wide range of data (structured, unstructured, numeric, text documents, video, audio, email, ticker data etc.)

By defining the problem to be solved, data analytics comprehends business. It recognises the information at hand and assesses its suitability for solving the business problem. It also prepares the data for usage by filling in gaps, fixing errors, and combining data sources, among other things. It makes valuable forecasts and explains business processes using a variety of algorithms.

Data analytics has a number of advantages. When vast amounts of data need to be kept, it saves businesses money by adopting tools like Hadoop and cloud-based analytics. The fast speed of tools and in-memory analytics allows firms to quickly identify new sources of information, allowing them to analyse data and make quick decisions based on the learnings. One can gain a far better knowledge of current market situations by analysing data.

Sentiment analysis is used by data tools to collect input on who is saying what about the company. It enables businesses to create new development prospects and entirely new business categories by combining and analysing industry data. It also recognises and improves business processes. E.g.- Retailers can quickly optimise their stock with the use of predictive models derived from social media data, web search trends, and weather predictions.

Data analytics is most commonly used in business-to-consumer (B2C) applications, where companies collect and analyse information about their customers, company processes, market economics, and practical experience. To assess trends and patterns, data is categorised, saved, and analysed. Knowledge analysis assists business managers in making educated decisions in order to move the company forward, enhance efficiency, raise profitability, and meet organisational objectives. Analytics is being used by cutting-edge companies across all industries to replace intuition and guesswork in decision-making. It delves into the approaches, concerns, and difficulties that come with analysing corporate data.

1.12.1 Data Driven Decision Making in SMEs

The thinking process of selecting a logical alternative from the given options is known as decision making. It's a decision made deliberately from a set of options in order to achieve organisational or managerial objectives or aims. Strategic decisions, management decisions, and everyday operational decisions are all part of the decision-making process. Every organisation must make several types of decisions, such as programmed vs. non-programmed decisions, frequent vs. infrequent decisions, operational vs. tactical vs. strategic decisions, individual vs. group vs. organisational decisions, and so on.

Customer satisfaction, commerce, and business operations are all evolving as a result of data analytics, presenting new opportunities and problems for SMEs. In SMEs, real-time knowledge streams will turbocharger utilisation analytics. The way the overall rules of doing business are changing due to new insights and a deeper grasp of client wants.

The tailored service is currently being reinvented by SMEs with affordable access to data. E-commerce with the intelligent application of knowledge, SMEs may anticipate and address client needs without the need for human involvement. Consumers' digital footprints disclose buying patterns, preferences, and interests — information that a typical local merchant would know from frequent human interactions with his customers. SMEs, unlike small firms, can utilise this information to customise offers and things we want.

The decision-making process is an ongoing and essential part of running any business or organisation. At every level of an organisation, decisions are continually being made. In business, decision-making entails making decisions or making compromises in order to meet company objectives. The quality of decision-making is said to be dependent on data accuracy and correctness, according to the literature. When information and processing quality improves, decision quality may improve or degrade. Process transformation and integration, skill development, retaining experience and human resources, guaranteeing data quality, adaptable systems, collaboration, information exchange, decision-maker quality, developing trust, and managing relationships are all elements that influence decision-making quality.

Modern business analytics tools have successfully integrated into existing organisational information systems and have become an intrinsic element of organisational business operations. Planning (analysing data to predict market trends for products and services), sourcing (procurement system, locating, negotiating, and assessing suppliers), manufacturing (timely inventory and production), and delivering are all areas where analytics is used (bringing products to plug more efficiently). Companies must, however, endure extensive business process modifications, employ change management strategies, and specialise in transforming downstream decision-making and business processes in order to fully utilise business analytics. Organizations today have access to a vast amount of data to analyse. Organizational structure and performance have been altered by digital technologies. As storage capacity has risen dramatically and knowledge collection methods have evolved, a vast amount of information has been readily available. Every second, new data is generated from a variety of sources. This data, which is large in volume, variety, and velocity, is stored and analysed in a variety of ways in order to extract value. To do so, several analytics are being used. Frameworks are created and used to connect data tools, architectures, and analytics to various decision-making stages. Valuable information is retrieved and used by using advanced analytic techniques on data to reinforce and support educated decisions.

Data analytics aid in the analysis and reporting of massive data sets (e.g., clearly understood dashboards and visualisations), enabling for better information transmission and creating a foundation for data-driven decision-making.

Knowledge analytics offers SMEs a wide range of benefits, including a deeper understanding of the interior production process, client and partner requirements, and the general features of national and native markets through marketing research tools. The impact of knowledge analytics and data-driven decision-making on enterprise performance primarily occurs through five channels: improving research and development (data-driven R&D); developing new goods and services using data as a product or as a serious input (data products and data-intensive products); optimising production or delivery processes (data-driven processes); improving marketing through targeted advertisement (data-driven marketing); and developing new organisations (data-driven organisations) (data-driven organization).

1.13 Conclusion:

Data analytics aids the organisation for findings and discoveries from multiple data sources; it breaks down a problem into smaller sections and acts as a filter for extracting meaning from the data collection, among other things. Better analysis leads to increased visibility and sound business strategy. With its numerous applications and wide-ranging use cases, data analytics is quickly becoming a keystone of strategic business decision-making. In addition to lowering business processes and inefficiencies, data and analytics play a significant influence. It aids in the discovery of a pattern within or between multiple data points. Insights and inferences can be gained from these patterns and relationships.

References –

[2]Enterprise (SME) Defined: Types Around the World by Daniel Liberto.

[1]Subrata Das (2013). Computational Business Analytics. CRC Press Chapman & Hall.

[3]Trewatha & Newport, (1982) Management, Dallas and Business Publication.

Chapter 2: Review of Literature

2.1 Introduction

A literature review is the documentation of a comprehensive assessment of published and unpublished work from secondary sources of data in areas of specific interest to the research, which aids us in determining future research scope that can be used by researchers in the future to improve the sector.

This chapter provides a thorough examination of the use of data analytics for decision-making in SMEs and other businesses. A thorough investigation was conducted to identify the numerous literatures available and to analyse the primary contributions and benefits for decision-making. Secondary data was gathered from a variety of sources, including journals, online databases, Ph.D. theses from various universities, and books. The following are some primary and secondary search sources:

- Science Direct
- INFLIBNET (Information and Library Network Centre) (scientific database journal)
- ELSEVIER
- Google Scholar (scholar.google.com)

There are two sections to the content. The first section is a review of Ph. D. theses from various universities on this issue, and the second half is a review of research papers, journals, books, and other materials.

2.2 Section I - Ph.D. Thesis from various universities

For their Ph. D. research studies, a number of research students have researched various parts of Data Analytics and its tools, as well as certain IT corporations that use these business analytics tools and some SMEs that use these business analytics tools to make business choices. The following are some of the sources:

Singh Mahendra (2018)[2] has completed his research in Supply Chain Management and Business Analytics and Information Technology. According to the researcher, supply chain management (SCM) studies are being given more weight. The value of operations management research has gained new approaches and dimensions in recent years, according to the researcher. He claimed that SCM is a well-known complicated management area. The efficacy of an organisation is directly influenced by SCM efficiency. The SCM function is critical for business performance and customer happiness. SC is made up of everyone who is involved in completing a customer's request, whether directly or indirectly. SCs are used to keep the various flows between suppliers, producers, and customers in check.

He clarified various terms, such as Business analytics (BA), also known as business intelligence (BI), big data (BD), and data analytics (DA), is a term used interchangeably in operations management and other domains such as information systems, computers science, and information technology. The business community prefers the word BA, whilst the IT community prefers the term BI. Academic scholars in the field of SCM, he claims, have demonstrated trends in the use of business analytics.

He added that advanced data analytics tools are being used in SC areas such as demand forecasting, sourcing planning, distribution planning, and sales reporting. IT is a set of tools and technology that aid in the collection, storage, processing, analysis, and reporting of data in a usable manner (information) for decision-making. Information system infrastructure plays a critical role in information sharing between SCs.

"The study was drawn from the unsolved topic of application of analytics in SCM of Indian plastics sector," the author concluded. There were several research gaps identified, including BA applications in operational functions, IT use for enhanced analytical skills, and a research agenda for examining the moderating effect of IT on SC performance. It was advised that the topic of regulating SC performance be investigated in order to learn how IT is crucial for the use of BA in SCM functions such as plan, make, source, deliver, and return areas as outlined in

[2] **Singh Mahendra (2018)** Business analytics and information technology in supply chain operational performances a study of Indian plastics industry, Banaras Hindu University

the SCOR model."

The study looked at how BA and IT are used in the Indian plastics industry. The applications of BA and IT in operational areas of SCM were studied using the different functional areas of SCM.

This research examines the relationship between Business Analytics and Information Technology in Supply Chain Management (SCM) by conducting a study of the Indian plastics industry and focusing on academic scholars in the field of SCM to show trends in business analytics application.

Filip Björkman and Sebastian Franco (2017)[3], The goal of the thesis was to look at the new technology of big data analytics and how it influences decision-making. Researchers conducted empirical research in the newspaper industry, which is experiencing a crisis due to declining revenues, the collapse of old business models, and the loss of traditional journalism jobs, prompting the industry to turn to big data analytics to stay competitive. The interview method was utilised to target three different industries that, based on our early information, were potentially undertaking big data analytics that influenced their decision-making.

From the analysis it was found that decision-making is becoming more transparent, accurate, efficient, and, to some extent, faster, according to the report. Furthermore, big data analytics has had an impact on the jobs in the organisations analysed, with editors becoming more like hybrids of analysts and editors, and journalists being given more responsibilities and evolving into multi-journalists.

Nalina. R (2017)[4]SME IT enterprises have been highlighted as potential contributors to

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[3]**Filip Björkman Sebastian Franco (2017)**, How big data analytics affect decision-making A study of the newspaper industry, Master's Thesis 30 credits Department of Business Studies Uppsala University

[4]**Nalina. R (2017)** An Analytical study on LOP and KMP their contributions towards Organizations competitive advantage among selected SME it companies in Bengaluru, Reva University

economic development, according to Author. Bengaluru was chosen as the location for her research because it is India's IT capital and the city with the most start-up enterprises. According to her, many IT businesses consider Bengaluru to be the most desirable location for their operations. The reasons for Bengaluru's selection are as follows: climatic conditions, geographical situations, and a significant number of previously existing organisations, as well as backing from government organisations and private company activities. The study focuses on this topic, as well as the main reason why SMEs in the IT industry are falling prey to the information war waged by larger organisations.

SME IT enterprises are regarded as the backbone of an economy for a variety of reasons, including the provision of employment opportunities, regional balance, poverty reduction, and entrepreneurial assistance, to name a few. Despite their tiny scale of operation, limited resources, and financial hardship, they have demonstrated the ability to become a profitable company any time soon until they lose against larger corporations.

The study suggests that acknowledging inter-conceptual and disciplinary reliance is more effective when organisations are located in similar cultural environments is critical. In terms of learning organising process and knowledge management practise combined in establishing competitive advantage in SME IT enterprises in Bengaluru, this study outperforms several empirically successful studies. In addition, the impact on organisational performance improvement was explored.

The strength of research in terms of providing sustenance, growth prospects, and associated benefits through gaining competitive advantage in SME IT enterprises in Bengaluru and to all other relevant beneficiaries was determined by the results of this research.

Khurana Vikas (2016)[5], in his research, author noted that Information Technology (IT) firms generate a large amount of business data, which is likely to double in bulk by the next decade. This data, he believes, should be processed and analysed before being made available to management for efficient and quality judgments. Organizations may swiftly create insights with

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[5]**Khurana Vikas (2016)** Analytical study on the impact of business intelligence tools on quality of decision making and organizational growth in select Information technology organizations At Pune, Savitribai Phule Pune University

the help of a business intelligence (BI) tool, allowing management to drive operational efficiencies, find newer opportunities, and differentiate themselves in a competitive market.
A survey of the literature finds that there is a gap in knowledge about whether Business Intelligence tools affect decision quality and organisational growth. The study's goal was to see how a business intelligence tool affected the quality of decision-making and organisational growth in IT companies in Pune.
The author came to the conclusion that BI tools are employed in all business functions inside the IT organisation. SAP Business Objects, Oracle BI, SAP BI/BW, and Home-grown analytics are the most often used BI tools in IT organisations, according to his research. The study discovered a link between BI tool, decision-making quality, and organisational growth, with BI tool having a favourable impact on decision-making quality and organisational growth.
From this research researcher understand on assessing the impact of BI tool-based quality decision making on choice categories (operational, tactical, and strategic), as well as the development of leadership attributes in managers. The survey also sought to determine the types of BI analytics that are employed in IT businesses, as well as the most essential BI analytics. It also looked into the relationship between the importance of BI analytics and its use.

Athula Balachandran (2014)[6]Content providers, CDNs (Content Delivery Networks), and network operators all have issues, according to author, and they are all attempting to better build and operate their networks in order to improve content delivery and provide a higher quality of experience. With the use of big data analytics, researchers discovered a novel way to address these issues. Large-scale analytics on user behaviour data can be used to inform the design of various components of content delivery systems, according to the researchers. In particular, it was demonstrated that insights gained from large-scale analytics can lead to better resource provisioning to supplement existing CDN infrastructure and deal with rising traffic. Furthermore, for developing predictive models based on machine learning approaches in order to comprehend users' quality expectations.
These models can be used to enhance the user experience. Similarly, even if they don't have

[6]**Athula Balachandran (2014)** Large Scale Data Analytics of User Behaviour for Improving Content Delivery, Carnegie Mellon University

access to client-side or server-side logs on user access patterns, mobile network operators can use large-scale data analytics techniques to extract user behaviour from network traces and build machine learning models that help them better configure the network for better content delivery. According to the researcher, implementing large-scale data analytics is a step forward in addressing some of the major issues that the various actors in the content distribution confront. With her research, she discovered that big data analytics and machine learning algorithms may be utilised to define user behaviour in the wild and inform various content delivery system design decisions.

The researcher learns how large-scale data analytics of user behaviour is used to improve content delivery through the usage of CDN infrastructure and machine learning models in this study.

Steven E. Whang (2012)[7]Data analytics has become an enormously essential and demanding subject in areas such as computer science, biology, health, finance, and national security, according to author's research. Scalable integration approaches are becoming increasingly crucial as large amounts of data become available for analysis. Simultaneously, new privacy concerns emerge, as massive amounts of data might quickly reveal one's sensitive information. The topic of entity relation (ER), which detects database records that refer to the same real-world entity, was originally discussed in the thesis.

Because of the recent expansion of data, ER has become a difficult problem in a variety of applications. The researchers offered scalable ER methodologies and new ER functions that had not before been investigated, as well as viewing ER as a black-box operation with universal techniques that may be applied across applications.

The researcher next discussed the difficulty of managing information leakage, which entails attempting to prevent key bits of data from being resolved by ER in order to protect data privacy. As more of our sensitive data is exposed to a variety of merchants, health care providers, employers, social media sites, and other entities, there is a greater chance that an adversary will be able to "connect the dots" and piece together our information, resulting in even more privacy loss. They proposed a measure for quantifying information leakage and the use of "disinformation" as a tool for containing information leakage.

[7]**Steven E. Whang (2012)** Data Analytics: Integration and Privacy, Stanford University

The researcher investigated and concluded the problem of information leakage and proposed disinformation techniques for reducing it. He formalised the disinformation problem by modelling the adversary as an ER process and proposed efficient algorithms for generating disinformation that causes the target cluster to merge with other clusters. Experiments reveal that deception strategies can considerably raise a target entity's bewilderment. The disinformation caused by right ER findings, according to the researcher, may be generally applied to other (correct) ER algorithms as well. In addition, the strategies function in the presence of incomplete data and can scale to enormous datasets. Disinformation approaches can be utilised as a framework for assessing ER resilience in general.
The researcher gained an understanding of Entity Relation (ER), which identifies data records and is a black box process, as well as the difficulty of managing information leakage, as a result of this investigation. It also covered topics such as data analytics, integration, and privacy.

2.3 Section II - Research papers and articles published in books, journals and periodicals

The researcher analysed and summarised the research papers and articles on Data Analytics and its tools in some SMEs with implementation for business decision making that were published in research journals, proceedings of national and worldwide level conferences, periodicals, and newspapers.

2.3.1 Problems Faced by SMEs While Implementing Big Data Analytics

Min Hooi Chuah and Ramayah Thurusamry (2021)[8], the study looked at the problems that Small and Medium Enterprises (SMEs) in Malaysia face while applying big data analytics. There are few studies that look at the relationship between Lessig's four modalities and the difficulty of implementing big data analytics. Based on the findings of a literature research, the study evaluated the implementation of Lessig's Four Modalities, namely the legal, architecture,

[8]**Min HooiChuah and Ramayah Thurusamry (2021),** Challenges of big data adoption in Malaysia SMEs based on Lessig's modalities: A systematic review, Cogent Business & Management, Volume 8, 2021 - Issue 1

social, and market challenges, for the adoption of big data analytics in Malaysian SMEs. Databases, journals, Google Scholar, and IEEE publications were used to search the literature. For this study, 21 papers were examined.

According to the study, there is a need to highlight a more thorough framework for recognising the issues faced by Malaysian SMEs, based on a review of existing literature studies in this subject.

SME require significant attention from both government and non-government groups in order to successfully manage these difficulties and convert them into opportunities to reach their full potential, according to the researcher. The study examined the challenges that Malaysian SMEs face, regardless of social, architectural, legal, or market constraints, and the necessity to enhance SMEs' survival rates in order to maximise their performance.

2.3.2 Benefit of Small and Medium-Sized Businesses Due to Big Data

Aparajita Dixit, Suresh Kumar Sharma and Durga Prasad Sharma (2021)[9], This study focused on why and how to use big data in micro, small, and medium-sized firms (MSMEs), describing storage elements of SME and MSME data on cloud for improved access to filtered data and data access efficiency. Small and medium-sized businesses, as well as MSME, can benefit from the potential of big data and business analytics.

The authors reviewed the role of MSMEs in the Indian economy and discussed issue areas in India, as well as various ideas to improve MSMEs' contribution to India's GDP through the use of big data. Indigo Airlines, Patanjali, and Krishi Jagaran-Magazine as developing environment MSME cases were investigated. According to the findings, big data analytics has become the most important component for almost all firms today. The proper application of big data aids the entrepreneur in making the best option at the correct time.

The researchers emphasised how small and medium-sized businesses can benefit from big data

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[9]**Aparajita Dixit, Suresh Kumar Sharma and Durga Prasad Sharma (2021),** Impetus on Big Data to Boost Indian MSME Sector and Economy using Cloud Storage, International Journal of Computer Applications (0975 – 8887), Volume 174 – No. 21

in terms of cost savings, competitive advantage, making accurate information available to entrepreneurs, better decision-making owing to the availability of accurate and timely data, and proven guidelines. MSME's can also leverage cloud-based big data analytics to accelerate their growth and obtain competitive advantages.

2.3.3 Whether SMEs can profit from big data in current economy

Lawrance Seseni and Charles Mbohwa (2021), the goal of this research was to look at how SMEs in emerging economies might profit from big data, as well as the limitations that SMEs face when adopting big data. The study was exploratory and focused on secondary data. It used a desk-review approach to analyse journal publications and government reports. The authors thoroughly explored the usage of big data by SMEs and described some of the problems associated with doing so. Researchers derived two research questions from the study: RQ1: How can big data help SMEs in emerging markets? RQ2: What are the hurdles that prevent SMEs in emerging markets from using big data?

According to the findings, SMEs find it difficult to use data analytical tools and technologies since they lack the necessary expertise and funds to purchase them. Big organisations and SMEs that employ big data analytics, on the other hand, are successful and have a better chance of boosting profits.

According to the authors of the report, training should be made available, and the government should provide financial and non-financial assistance to SMEs so that they can purchase and employ big data tools and technologies.

Xuemei Li (2021), the study was based on secondary data and tried to determine the usefulness and application of business analytics (BA) in E-commerce, as well as the problems and trends connected with BA in E-commerce. It looked into the literature on BA in depth, with a specific focus on E-commerce.

This study proposes an E-commerce BA research model that describes the iterative BA process from data to analysis, decision, and estimation, and divides BA analysis outcomes into functional and competitive levels.

Preeti Sharma, Kartikey Nigam (2020)[10], the goal of this study was to determine current market trends and the future deployment of BDA (Business Data Analytics) in OM (Operations Management), as well as to outline research gaps in the domain using text analytics. The research was based on secondary data, and the authors used 68 research articles from various journals published between 2010 and 2020. These were used to create a word cloud in order to evaluate significant textual data points and to research academic papers conducted in OM utilising BDA. Emerald Insight, Wiley Online Library, Google Scholar, and the research gate database were used to gather secondary data. The majority of the publications were published in supply chain management, specifically in the logistics field, according to the research.

The research also demonstrated how BDA is being used in fields including cold-chain logistics, identifying indicators linked to cargo loss in shipping companies, and breakthroughs in urban transportation utilising Big Data.

The use of Big Data in demand forecasting, inventory management, supply chain management, and transportation management is understood by the research writers.

2.3.4 To Understand Data Analytics Trends in SMEs

Dr. Muzaffar Asad, Dr. Naveed Altaf, Dr. Aqeel Israr, Ghiasul Hassan Khan (2020)[11], This research is being carried out to better understand data analytics trends in SMEs. To understand the trends, bibliometric analysis was employed. The authors used the Scopus database to conduct this bibliometric analysis. For the analysis, a total of 241 documents were chosen. Matrixes were calculated using Harzing's Publish and Perish programme. The frequency and percentages were then calculated in Excel. The graphics were sourced from the Scopus

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[10]**Preeti Sharma, Kartikey Nigam (2020),** Use of Big Data Analytics in Operations Management: A Review Using Text Analytics, MDIM Business Review, Volume: I, Issue II, ISSN (Online) 2564-8555

[11]**Dr. Muzaffar Asad, Dr. Naveed Altaf, Dr. Aqeel Israr, Ghiasul Hassan Khan (2020),** Data Analytics and SME Performance: A Bibliometric Analysis, t: https://www.researchgate.net/publication/348640551

database.

The bibliometric analysis of the examined literature revealed that there is a need to create theory, because the majority of research believed data analytics to be a source, but in fact, information is the source, but this is a technique that may be used optimally.

According to the findings, there is a need to identify the challenges that countries such as Pakistan, Jordan, and Nigeria face when adopting data analytics, which should be identified in future studies and overcome by governmental authorities, and the authority of data analytics should be linked with strategic orientations of SMEs.

2.3.5 To Examine the Issues & Solutions of Big Data for Small Business

Shouhong Wang , Hai Wang (2020)[12], The goal of this study was to define the synergistic link between big data and knowledge management (KM), analyse the issues and IT solutions of big data for small businesses, and build a big data KM model for small businesses based on the real-world business cases collected. The researchers gathered eight well-documented cases of successful big data analytics in small businesses and conducted a qualitative data analysis of these cases in the context of knowledge management. The qualitative data analysis of the various situations indicates a big data KM model for small businesses.

The study contributed to the KM literature by proposing a theoretical model of big data KM for SMEs based on the underlying elements of strategic data utilisation, knowledge guided big data project planning, SME IT solutions, and new knowledge products.

Muhammad Qasim Shabbir, Syed Babar Waheed Gardezi (2020)[13], the function of knowledge management practises (KMP) as a mediating factor in the application of big data

[12]**Shouhong Wang , Hai Wang (2020),** Big data for small and medium-sized enterprises (SME): a knowledge management model, Journal of Knowledge Management, ISSN: 1367-3270

[13]**Muhammad Qasim Shabbir, Syed Babar Waheed Gardezi (2020),** Application of big data analytics and organizational performance: the mediating role of knowledge management practices, Journal of Big Data, Article number: 47 (2020), https://journalofbigdata.springeropen.com/articles/10.1186/s40537-020-00317-6

analytics (ABDA) and organisational performance is investigated in this study (OP). A customised instrument was used to collect data from respondents working in SMEs. The information was gathered from a variety of SMEs operating in Pakistan. The sample size was 230, and 210 questionnaires were satisfactorily filled and returned. With descriptive analysis, a 5-point Likert scale was used.

Mediation may not be viable if any one non-significant association is discovered, it was concluded according to the study.

According to the findings, knowledge management methods serve a partial mediation role, which is a novel result in the big data and organisational performance literature, and has never been examined in the context of SMEs in any developing nation.

Bernd Britzelmaier, Carolin Graue, Matthias Sterk (2020)[14], the goal of this research was to examine the importance, problems, and opportunities of big data analytics for small and medium-sized businesses (SMEs) in Germany. The study used secondary data to answer questions such as: how important is big data analytics for SMEs? What are the problems and risks, as well as opportunities and potentials, associated with big data? And who can take over responsibility for big data operations in SMEs? This research focused on the business context. The technological domain, on the other hand, or the in-depth investigation of certain IT technologies, received less attention.

The qualitative study, according to the researcher, has provided a comprehensive picture of big data's current state in SMEs.

2.3.6 To Study the Association Between Data Mining and SMEs

Tariq Saeed (2020)[15]**,** The first part of the article looked at the relationship between data mining and economic development in Small and Medium Enterprises (SMEs). According to the report,

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[14]**Bernd Britzelmaier, Carolin Graue, Matthias Sterk (2020),** Big data in SMEs – findings of an empirical study, Global Business and Economics Review, Vol. 22, Nos. 1/2, 2020

[15]**Tariq Saeed (2020),** Data Mining for Small and Medium Enterprises: A Conceptual Model for Adaptation, Intelligent Information Management > Vol.12 No.5, September 2020, Scientific research

each SME should start small with an internal data mining exercise to digitalize and analyse their customer data, then scale up as the company expands and gets the resources needed to manage any system properly. The most prevalent process framework for data mining for SMEs is the (CRISP-DM) Cross Industry Standard Process for Data Mining model, according to the author. The article concluded that data mining is a strategy that must be scaled up with the size of the firm over time for any SME. The report identifies a number of significant obstacles that any SME must overcome before embracing data mining.

Ying Liua, Anthony Sorokab, Liangxiu Hanc, JinJiand, Min Tange (2020)[16],

2.3.7 To Study How SMEs Analyse the Relationship Between Customer Data & Product Design

Manufacturing SMEs in the UK's South Wales and Greater Manchester industrial sectors are studied, as well as their possible incentives for employing and knowledge of big data-based customer analytics. An exploratory survey was undertaken to learn more about the types of customer data they have, storage methods, customer data volume, and so on. An exploratory study was conducted to learn how SMEs view the relationships between customer data and product design, as well as their expectations for large customer data analytics and the problems they face in maximising the value of big consumer data. Primary data was gathered by analysing consumer internet reviews and the capacity of two focus groups of 30 people to acquire customer insights and make strategic decisions.

The study concluded that SMEs considering implementing big data and customer analytics must consider a variety of managerial and technical considerations. The study encourages SMEs to embrace big customer data and suggests that a cloud-based approach may be the most appropriate way of providing access to big data analytics techniques.

Juane Maritz, Sunet Eybers, Marie Hattingh (2020)[17], BDA (Big Data Analytics)

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[16]**Ying Liua, Anthony Sorokab , Liangxiu Hanc , JinJiand , Min Tange (2020),** Cloud-based Big Data Analytics for Customer Insight-driven Design Innovation in SMEs, International Journal of Information Management 51 , 102034. 10.1016/j.ijinfomgt.2019.11.002 file

[17]**Juane Maritz, Sunet Eybers, Marie Hattingh (2020),** Implementation Considerations for Big Data Analytics (BDA): A Benefit Dependency Network Approach, Conference on e-

implementation considerations for new BDA endeavours were highlighted in the paper, which will assist organisations in aligning their BDA efforts with their entire company strategy to maximise business value. A structured literature review was undertaken concentrating on investment targets, business benefits, enabling changes, and IT enablers while adopting BDA, using the Benefit Dependency Network (BDN) model as the theoretical basis.

Based on the foundation of BDN, the research provided a guideline to organisations implementing BDA, and a BDN model approach can assist in identifying organisational technology considerations.

Patrick Mikalef, Ilias O. Pappas, John Krogstie, and Paul A. Pavlou (2019)[18], the study relied on secondary data. The authors developed a research framework for resource management in big data and business analytics, as well as data attributes sources and analytics approaches. The authors also went into great detail about the business value of big data and business analytics, as well as the mechanisms and moderators involved. The authors analysed 53 distinct literatures on big data and business analytics from various perspectives, adding depth to the topic and creating some intriguing implications for research and practice.

Researchers comprehend the phenomenon of big data and business analytics as well as how firms may develop and capture value from their data resources as a result of their research.

2.3.8 To Conduct Meta-Analysis of Practical Studies on Big Data Analytics and Performance of Organisation

Mihai BOGDAN, Anca Borza (2019)[19], the goal of the research was to conduct a meta-analysis of empirical studies on big data analytics and organisational performance. The research was based on secondary data, and researchers looked at 37 articles indexed on ISI Web of

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Business, e-Services and e-Society

[18]**Patrick Mikalef, Ilias O. Pappas, John Krogstie, and Paul A. Pavlou (2019),** Big data and business analytics: A research agenda for realizing business value, Article in Information & Management, : https://www.researchgate.net/publication/337543997

[19]**Mihai BOGDAN, Anca Borza (2019),** Big Data Analytics and Organizational Performance: A Meta-Analysis Study, Management and Economics Review, Volume 4, Issue2.

Knowledge between January 2010 and May 2019. Researchers objectively investigated the influence of big data analytics on organisational performance using a meta-analysis.
The study concluded that, Big data analytics has a positive impact on organisational performance.
According to the findings of the survey, a big data effort is a key feature for enterprises to gain from, and in order to implement this revolution, resources must be put in place, and employees and managers must develop new skills and behaviours.

2.3.9 Evaluation of Current Development, Opportunities, Drawbacks of Big Data

Ifeyinwa Angela Ajah and Henry Friday Nweke (2019)[20], Based on accessible literature, the study evaluated and discussed recent developments, opportunities, and drawbacks of big data, as well as how it has enabled firms to create successful business strategies and remain competitive. The evaluation discussed several big data and business analytics applications, as well as the data sources provided by these apps and their main properties. The assessment emphasised the problems of implementing big data projects successfully, as well as the current open research directions in big data analytics that need to be considered further.
According to the authors of the report, good data management and manipulation using big data methodologies and technologies can give actionable insights that generate business value.

2.3.10 To Examine Whether Performance Improved Due to Investments in Big Data Analytics

Patrick Mikalef, Maria Boura, George Lekakos, John Krogstie (2019)[21], The study looked

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[20]**Ifeyinwa Angela Ajah and Henry Friday Nweke (2019),** Big Data and Business Analytics: Trends, Platforms, Success Factors and Applications, big data and cognitive computing, MDPI
[21]**Patrick Mikalef, Maria Boura, George Lekakos, John Krogstie (2019),**
Big data analytics and firm performance: Findings from a mixed-method approach, Journal of Business Research, Volume 98
Parisa Maroufkhani, Ralf Wagner, Wan Khairuzzaman Wan Ismail, Mas Bambang Baroto and Mohammad Nourani (2019)[21],

into the resource configurations and contextual elements that contribute to performance improvements from big data analytics investments. 175 chief information officers and IT managers from Greek companies provided the primary data. Three case studies were investigated.

According to literature surveys and research studies, organisations must establish strong big data analytics capabilities in order to exploit big data analytics and reap performance advantages.

The study discovered four distinct patterns of factors around big data analytics that contribute to excellent performance by using a fuzzy-set qualitative comparative analysis (fsQCA) method on quantitative data.

The goal of the research is to compile a comprehensive list of contributions linked to big data analytics and company performance. The elements that may impact the adoption of big data analytics in various parts of an organization were discovered in this study, as well as the numerous types of performance that big data analytics can address. The authors reviewed a variety of literatures relating to data analytics and company performance, and the review provided both academics and practitioners with a better knowledge of the relationship between big data analytics and business performance.

By highlighting the role of big data analytics in boosting business performance, the authors have conducted several literature reviews. These reviews offer to open up paths for both conceptual and empirical research streams.

2.3.11 The Importance of Data Analytics in the Current Digital Revolution

Marco Bianchini and Veronika Michalkova (2019)[22], the report examined policy examples from throughout the OECD and provided an overview of the main trends, possibilities, and problems in the use of data analytics tools by SMEs. The research was based on secondary data, and the authors went into great detail about the significance of data analytics in the ongoing

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[22]**Marco Bianchini and Veronika Michalkova (2019),** Data Analytics in SMEs: Trends and policies, OECD SME and Entrepreneurship Papers No. 15, ISSN: 26164353 (online) https://doi.org/10.1787/f493861e-en

digital revolution, as well as its potential for improving SME performance, such as productivity. The study concluded with evidence on the usage of data analytics in SMEs, a discussion of the main internal and external hurdles to SMEs using data analytics, and an illustration of policy methods to encourage SMEs to make data-driven decisions.

Muhidin Mohamed, Philip Weber (2016 to 2019)[23], The study presents lessons learned from a case study of 53 UK SMEs, mostly from the West Midlands region of England, who were supported in the areas of big data management, analytics, and related IT issues as part of a three-year ERDF (European Regional Development Fund) project called Big Data Corridor. This study presents numerous viewpoints based on the survey's sample organizations, including digital technology trends, problems affecting UK SMEs, and the state of their usage of data analytics and big data. The top ten business sectors among the 53 SMEs from 18 different industries were examined, including consultation, technology, education and training; marketing, manufacturing, and so on.

A brief review of digital and data usage patterns, as well as some lessons learned from a case study of 53 UK SMEs, were included at the end of the report. The difficulties that SMEs have in discovering the hidden value of big data are also explored.
The researcher believes that if SMEs are given the proper skills and/or financial support, they will be able to fully utilise data to help them, and thus the entire economy, flourish.

2.3.12 To Focus the Issues Related to Standardisation of Process and Data Analytics

Michael Dittert, Ralf-Christian Härting, Christopher Reichstein, Christian Bayer (2018)[24]

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[23]**Muhidin Mohamed, Philip Weber (2016 to 2019),** Trends of digitalization and adoption of big data & analytics among UK SMEs: Analysis and lessons drawn from a case study of 53 SMEs, https://lorilewismedia.com/

[24]**Michael Dittert, Ralf-Christian Härting, Christopher Reichstein, Christian Bayer (2018),** A Data Analytics Framework for Business in Small and Medium-Sized Organizations, : https://www.researchgate.net/publication/318101009

Many small and medium-sized businesses are still oblivious to the benefits of process standardisation and data analytics. The primary causes for this are a lack of business prioritisation, a lack of (IT) competence, and a lack of understanding of Data Analytics concerns. To address these issues, the authors created a suitable data analytics process architecture for SMEs. And, as part of the investigation, the authors examined a case study that focused on data mining, which is the most important domain of Data Analytics. The KDD process, CRISP-DM, and SEMMA process frameworks were discussed.

According to the findings, data analytics will be a valuable tool for SMEs. Furthermore, the process framework enables small and medium-sized businesses to enter the field of data analytics with a low entry barrier, reducing the need for significant costs and external specialists. It allows SMEs to take use of their data and engage in Big Data analysis.

2.3.13 To Examine Obstacles for Adoption of Big Data Analytics in SMEs

Siti Aishah Mohd Selamat, Simant Prakoonwit, Reza Sahandi, Wajid Khan, Manoharan Ramachandran (2018)[25],Despite the fact that data mining is widely employed in the transportation sector, the necessity for SMEs to implement data analytics has reached a critical point. "Knowledge Discovery in Database" (KDD), "Sample, Explore, Modify, Model, and Assess" (SEMMA), and "Cross Industry Standard Process for Data Mining" are three popular data mining models used by significant organisations in the transportation sector, according to the research (CRISP-DM). The same models were discovered in the context of SMEs in numerous industries. The study relied on secondary data, and the authors thoroughly examined SMEs Adoption Barriers in Big Data analytics.

The article suggests that a fresh paradigm is urgently needed to meet the needs of SMEs, particularly in the transportation sector.

According to the report, SMEs can increase their productivity by up to 6% by using data analytics in their organisation. CRISP-DM is the most common DM model used by SMEs in

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[25]**Siti Aishah Mohd Selamat, Simant Prakoonwit, Reza Sahandi, Wajid Khan, Manoharan Ramachandran (2018)**Big data analytics—A review of data-mining models for small and medium enterprises in the transportation sector

the transportation sector, and it is mostly utilised for prediction and decision-making process facilitation.

Naoyuki Yoshino and Farhad Taghizadeh-Hesary (2018)[26], the report identifies the challenges that SMEs have in obtaining financing and proposes solutions to address them. The development of credit information infrastructures for SMEs and the use of credit-rating techniques for SMEs to address the asymmetric information problem, as well as the development of a sustainable credit guarantee scheme to solve the collateral issue of SMEs and ease their access to finance, are the remedies proposed in this paper.
SME's have a vital role in Asian economies, according to the report, as they account for a large percentage of employment and output in all Asian countries. SMEs, on the other hand, find it difficult to obtain low-cost financing in Asia's bank-dominated financial systems.

2.3.14 Impact of Business Analytics on Financial and Operational Performance

Vincent Whitelock (2018)[27], This study provided a simplified flow chart of a business analytics process for data acquisition, data management, and data-driven decision-making, as well as a comprehensive, theoretical framework to explain the key types of business analytics, their relationships, and how business analytics use impacts operational and financial performance. Using five primary forms of business analytics, the study also proposed a cost-effective approach that can be used to small, mid-sized, and large businesses.
According to the study's findings, companies that are "overwhelmed by" and "struggling to use" data to better business results have a realistic, cost-effective framework in place to expand their business analytics capabilities.

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[26]**Naoyuki Yoshino and Farhad Taghizadeh-Hesary (2018),** THE ROLE OF SMES IN ASIA AND THEIR DIFFICULTIES IN ACCESSING FINANCE, Asian Development Bank Institute, ADBI Working Paper Series

[27]**Vincent Whitelock (2018),** Business analytics and firm performance: role of structured financial statement data, Journal of Business Analytics, Volume 1 Issue 2

2.3.15 Influence of Culture of Big Data Analytics on Management Decisions

UsaratThirathon, Bernhard Wieder, Zoltan Matolcsy, Maria-LuiseOssimitz (2017)[28].

The study looked into how Big Data, analytics, and analytic culture influence management decision-making. Because the study is exploratory in nature, a cross-sectional survey was chosen as the most appropriate research method. The poll targeted CIOs and senior IT managers of Australia-based medium to large for-profit firms and distributed questionnaires to 174 people.

According to the findings, companies with a strong analytical culture can exploit this resource as a competitive advantage. Finally, the research shows that managers in smaller firms are substantially more likely than managers in bigger organisations to base their decisions on analytic results, implying that the former employ analytics to stay competitive versus their larger counterparts.

Marilex Rea Llave (2017)[29], Small and medium-sized enterprises (SMEs) are still trailing behind in the adoption of BI&A, according to research. 62 publications about BI&A in SMEs were gathered, categorised, summarised, and analysed in this paper. The study was based on a variety of sources. Cloud BI&A, in addition to open-source solutions, was seen as a low-cost licenced alternative for SMEs.

The study stated that it offered a thorough evaluation of the literature on BI&A in SMEs. This gives promising evidence for practitioners' contributions, which they can use to drive their future endeavours. This can assist BI&A suppliers improve their solutions by improving usability, integration with other systems, and simplicity of implementation, for example.

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[28]**Usarat Thirathon Bernhard Wieder Zoltan Matolcsy Maria-Luise Ossimitz (2017),** Big Data, Analytic Culture and Analytic-Based Decision Making – Evidence from Australia, CENTERIS - International Conference on ENTERprise Information Systems ScienceDirect, Procedia Computer Science 121 (2017) 775–783

[29]**Marilex Rea Llave (2017),** Business Intelligence and Analytics in Small and Medium-sized Enterprises: A Systematic Literature Review, Procedia Computer Science 121 (2017) 194–20, Science Direct

2.3.16 Interaction Between SMEs & BI

Shaheb Ali Shah J. Miah Shahadat Khan (2017)[30], the goal of this study was to take a holistic look at prior research by conducting a theoretical examination of how BI and SMEs interact. As a result, this research was necessitated and an attempt was made to review the literature in regard to theoretical conclusions. The role of business intelligence and the relationship between SMEs and BI were thoroughly examined by the authors.

The authors of the study found that a literature evaluation reveals that SMEs' owners/managers are being pushed to adopt new business policies due to changing environmental conditions. In addition, the study looked at BI deployment in SMEs for data management and decision-making. The study also discovered that the interactive relationship between BI and SMEs provides a source of learning, bolstering their individual positions.

2.3.17 To Study RdM, Big Data Analytics and Issues Related It

Anthony Sorokaa, Ying Liu, Liangxiu Han, Muhammad Salman Haleem (2017)[31],
Manufacturing business models, strategies, methods, and technologies that shift the economics and structure of manufacturing, particularly in relation to location and scale, are referred to as redistributed manufacturing (RdM). The findings of an early exploratory survey of manufacturing SMEs in the United Kingdom were presented in this study. Considering their background and current status, as well as their current knowledge and interests in RdM, big data analytics, and related issues. The research was based on both primary and secondary sources of information. For the study, industrial companies were asked to complete 15 online surveys. Qualitative research was used in this study. The authors also explored some of the problems that small businesses face when it comes to big data analytics.

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[30]**Shaheb Ali Shah J. Miah Shahadat Khan (2017),** Analysis of Interaction between Business Intelligence and SMEs: Learn from Each Other, JISTEM - Journal of Information Systems and Technology Management, • https://doi.org/10.4301/S1807-17752017000200002

[31]**Anthony Sorokaa, Ying Liu, Liangxiu Han, Muhammad Salman Haleem (2017),** Big data driven customer insights for SMEs in redistributed manufacturing, ScienceDirect, The 50th CIRP Conference on Manufacturing Systems

According to the findings, there may be some need for big data analysis. It's likely that current solutions won't work for SMEs, and that SMEs are unprepared and unequipped to take advantage of what big data analytics has to offer.
According to the findings, more research into the demands of manufacturing SMEs, as well as big data analytics and RdM, is required.

2.3.18 Perception of Big Data and Its Issues of Application in Manufacturing SMEs

S. Shah, C. Bardon Soriano, A.D. Coutroubis (2017)[32], The purpose of this research was to present an investigation into the notion of Big Data and its application issues in manufacturing SMEs. The report has offered a critical strategic point for SMEs to investigate Big Data. The authors provided technological, managerial, and economic issues of big data within manufacturing organisations in their article, which was based on secondary data.
The study looked into the usage of a case study approach for repurposing, adopting, and comprehending strategic future directions based on the findings. Because of their practicality and flexibility in the market, the study concentrated on SMEs.

2.3.19 The Study to Uncover SME Specific Indicators of Business Intelligence Competence

Umar Bin Qushem, Akram M. Zeki, Adamu Abubakar (2017)[33], The goal of the study was to uncover Small and Medium Enterprise (SME)-specific determinants of Business Intelligence efficiency, which would lead to a better knowledge of BI framework creation and testing in the business world for those businesses. In this study, extensive literature studies were used to assess the efficiency aspects and a holistic conceptual framework was provided. The study focused on Malaysia and employed descriptive statistics. A total of 200 surveys were distributed

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[32]**S. Shah, C. Bardon Soriano, A.D. Coutroubis (2017),** Is Big Data for Everyone? The Challenges of Big Data Adoption in SMEs, IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)

[33]**Umar Bin Qushem, Akram M. Zeki, Adamu Abubakar (2017),** Successful Business Intelligence System for SME: An Analytical Study in Malaysia, International Research and Innovation Summit (IRIS2017)

to BI firms, with 55 forms returned, 55 of which were rated helpful and full.
The findings suggested that SMEs should concentrate on the environmental factor (EF), since it is the most identified element that leads to BI efficiency in businesses.

2.3.20 The Success Factors of Business Analytics

Rachida F. Parks, Ravi Thambusamy (2017)[34], Executives and professionals in business analytics, such as the Chief Data Officer (CDO), Chief Information Officer (CIO), Chief Privacy Officer (CPO), Chief Medical Information Officer (CMIO), Chief Executive Officer (CEO), and Managers, were interviewed in semi-structured interviews. The study used 17 interviews with 18 informants from 15 organisations in the United States. The authors employed a qualitative-empirical research approach and offered many literatures on the factors of Business Analytics Success.
The study came to a conclusion with a significant contribution from business analytics, which employs a grounded theory methodology to provide a rich lens through which to examine business analytics success factors and impact.

2.3.21 Boundaries and Benefits of Delivering Big Data Analytics through Cloud Computing

Bala M. Balachandran and Shivika Prasad (2017)[35], the benefits and limitations of delivering big data analytics through cloud computing are outlined in the article. The storage and computational requirements of big data analytics can be met with cloud computing. The authors examined how combining these two dominating technologies might improve big data mining,

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[34]**Rachida F. Parks, Ravi Thambusamy (2017),** Understanding Business Analytics Success and Impact: A Qualitative Study, Information Systems Education Journal (ISEDJ), ISSN: 1545-679X

[35]**Bala M. Balachandran and Shivika Prasad (2017),** Challenges and Benefits of Deploying Big Data Analytics in the Cloud for Business Intelligence, ScienceDirect, International Conference on Knowledge Based and Intelligent Information and Engineering Systems, KES2017

allowing organisations to better decision-making processes, as well as the challenges and hazards that need be addressed when employing a cloud-based service model known as CLaaS. The authors described the cloud computing paradigm, as well as cloud deployment and cloud service delivery methods, using secondary data. The study has revealed the advantages of big data as well as its drawbacks.

The study concluded that cloud computing may help organisations stay competitive by providing a variety of benefits; however, before investing in cloud-based big data analytics, a company must fully comprehend the scope of the project. An organization's investment in cloud analytics can be rewarding, but appropriate planning is required to guarantee that all phases of analytics are covered.

2.3.22 Factors Affecting Growth of SMEs

Asini Udani Amaradiwakara, M. M. Gunatilake (2016)[36], The paper is based on both primary and secondary sources of information. In the Gampaha District of Sri Lanka's Western Province, the population of this study is made up of SMEs in various industries such as food, clothing, metal and machinery, and so on. This research was conducted in the Western Province. A total of 100 businesses were included in the survey sample. The stratified sampling approach was used to pick the sample. A questionnaire and face-to-face informal interviews with SME owners were used to gather primary data. Research articles, Census and Statistics Department publications, debt financing institutions, CBSL annual reports, and the internet were used to gather secondary data.

According to the findings, the growth of Sri Lankan SMEs is influenced by a variety of factors. The expansion of SMEs in Sri Lanka has been hampered by a number of problems. Financial deficiency has hampered the growth and expansion of small and medium-sized businesses.

According to the findings of the study, the majority of Sri Lankan SMEs have limited access to the foreign market and focus solely on the domestic market, which has hampered their growth.

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[36]**Asini Udani Amaradiwakara, M. M. Gunatilake (2016),** Factors Affecting Growth of Small and Medium Enterprises in Sri Lanka, Journal of Business & Economic Policy, Vol. 3, No. 4; ISSN: N 2375-0766

2.3.23 The Association of Big Data Analytics for Improved Business Intelligence for the Data Obtained from Social Media

Jiwat Ram, Changyu Zhang, Andy Koronios (2016)[37], The focus of the research was on the function and implications of Big Data analytics in the context of business intelligence. This research addressed this knowledge gap by investigating the function and implications of Big Data analytics on business intelligence for data acquired from Chinese social media networks. The research was exploratory in nature, with data gathered via questionnaires and interviews. Researchers gathered information from roughly 35-40 interviews with respondents from a variety of industries, including retail and manufacturing, including IT managers, IT consultants, and Senior Business Managers.

In the context of Chinese firms, the study looked at the implications of Big Data analytics of data obtained from social media for improved business intelligence. In China, social media and online business have risen at an exponential rate over the previous decade, presenting an opportunity to investigate how data obtained through these channels might be used to improve business.

2.3.24 How the Obstacles can be Overcome by Using Various Tools for Adoption of BI System

Raghavendra Raj, Shun Ha Sylvia Wong and Anthony J. Beaumont (2016)[38], The paper looked at the challenges of adopting a BI system in a UK SME, such as a lack of technical skills and a limited budget. Authors explained how these obstacles can be overcome by using various tools and tactics, as well as the potential rewards, based on their experiences in dealing with

[37]**JiwatRam, Changyu Zhang, Andy Koronios (2016),** The implications of Big Data analytics on Business Intelligence: A qualitative study in China, Fourth International Conference on Recent Trends in Computer Science & Engineering, Procedia Computer Science 87 (2016) 221 – 226, Science Direct

[38]**Raghavendra Raj, Shun Ha Sylvia Wong and Anthony J. Beaumont (2016),** Business Intelligence Solution for an SME: A Case Study, - 8th International Conference on Knowledge Management and Information Sharing, ISBN: 978-989-758-203-5

these concerns. The article was based on secondary data, and the authors offered extensive information on BI components, BI vendors, BI usage, and BI systems, as well as some issues that SMEs face while implementing BI.

The study stated that while installing a BI solution is an iterative and difficult process, BI solutions give analytic data and essential performance information that allows businesses of all sizes to be managed efficiently.

According to the authors of the survey, SMEs recognise the value of simplifying their information resources to assist them in making critical business decisions. They're also aware that there are numerous BI products on the market. However, many SMEs do not have access to these technologies. As a result, SMEs are hesitant to invest time and money in BI solutions due to a general lack of IT budget.

2.3.25 Practice of Big Data for Open Innovation Strategies

Pasquale Del Vecchio, Alberto Di Minin, Antonio Messeni Petruzzelli, Umberto Panniello, Salvatore Pirri (2016)[39].

The study focused on two categories of businesses: small and medium-sized businesses (SMEs) and large organisations. The authors have compiled a useful overview of the main trends, possibilities, and obstacles that SMEs and large enterprises face when implementing open innovation strategies using Big Data. The authors evaluated numerous literatures on big data in major organisations and gave a comparison of open innovation in the age of big data: SMEs vs large enterprises, including trends, possibilities, and problems.

The researchers highlighted the main trends, opportunities, and challenges that large enterprises and SMEs confront through their research. They also discussed how Big Data analysis may be used to improve the innovation process in cases where it is substantial and profitable.

Researchers used the findings of the study to fill a vacuum in the literature by providing a complete review of the usage of Big Data for open innovation initiatives.

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[39]**Pasquale Del Vecchio, Alberto Di Minin, Antonio MesseniPetruzzelli, Umberto Panniello, Salvatore Pirri (2016),** Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges, SPECIAL ISSUE ARTICLE, WILEY

2.3.26 How Business Analytics Tools Are Beneficial to Improve Performance of Business

Dinesh E and Dr. Vetrivel T (2016)[40].

Business Analytical Tools are critical for leaders' guidance and support. Small and medium-sized businesses, as well as major corporations and multinational corporations, can benefit from these business analytics tools to improve their performance. As a result, the study examined various sorts of business analytics models, including intelligence and business analytics. In addition, the study explored the many forms of business analytics used in various domains. The research was based on secondary information.

According to the findings of the study, business analytics is a critical component in unlocking the organization's profit door. Business analytics tools are extremely helpful in enhancing the accuracy of forecasts and making business choices for all types of enterprises.

DorukSen, Melike Ozturk, Ozalp Vayvay (2016)[41], The goal of the study is to lay the groundwork for future Big Data research for SMEs by examining the major opportunities and dangers that must be addressed. The study relied on secondary data. The authors explored the 5Vs, which are large volume, high velocity, high variety, poor veracity, and high value, and evaluated several literatures on big data and SMEs. Big data, according to the report, can provide prospects for in-depth analysis of SMEs' own data, as well as competitive knowledge.

The application and usage of big data, according to the researcher, may very well become the next stage of innovation in corporations and SMEs alike, allowing for a greater level of strategic management and increasing organisations' competitive position by generating future opportunities.

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[40]**Dinesh E and Dr. Vetrivel T (2016),** “Business Analytics: Opportunities for Small and Medium Enterprises”, Asian Journal of Research in Social Sciences and Humanities, Vol. 6, No. 6, ISSN 2249-7315

[41]**DorukSen ,Melike Ozturk , OzalpVayvay (2016),** An Overview of Big Data for Growth in SMEs, 12th International Strategic Management Conference, ISMC 2016, 28-30 October 2016, Antalya, Turkey, Procedia - Social and Behavioral Sciences 235 (2016) 159 – 167, Science Direct

Vajjhala & Ramollari (2016)[42]Believes that the availability of cloud computing solutions for Big Data management is a potential for all businesses, particularly SMEs, whose financial and organisational resources are generally restricted.

Researchers can learn about cloud computing options for Big data management for SMEs with limited financial and organisational resources by reading this paper.

2.3.27 Study of Big Data by Integrating Managerial and Technological Dimensions

De Mauro et al. (2016)[43]have attempted to present a preliminary systematisation of the Big Data debate by integrating the technological and managerial dimensions, and emphasising the value generation from the transformation of such huge data assets as the primary problem for businesses. The phenomenon's intricacy, as well as the necessity to understand its consequences for company value development, necessitates a far deeper comprehension.

The researcher gained an understanding of the topic about big data by connecting two factors: technology dimension and managerial dimension, and discovered that value creation is the key difficulty for businesses.

Shirley Coleman, Rainer Göb, Giuseppe Manco, Antonio Pievatolo, Xavier Tort-Martorell and Marco Seabra Reis (2016)[44]**,** All stakeholders, including national and international policymakers, IT, business management, and data science communities, face a complicated problem as a result of the impediments to SME adoption of big data analytics, according to the report. The study also presented a big data maturity model for SMEs as a first

[42]**Vajjhala, N. R., & Ramollari, E. (2016).** Big Data using cloud computing – Opportunities for small and medium sized enterprises. European Journal of Economics and Business Studies, 4, 129–137.

[43]**De Mauro, A., Greco, M., & Grimaldi, M. (2016).** A formal definition of Big Data based on its essential features. Library Review, 65, 122–135.

[44]**Shirley Coleman, Rainer Göb, Giuseppe Manco, Antonio Pievatolo, Xavier Tort-Martorell and Marco Seabra Reis (2016)**, HOW CAN SMES BENEFIT FROM BIG DATA? CHALLENGES AND A PATH FORWARD, Quality and reliability engineering international, (32), 6: 2151–2164."

step toward developing a data analytics roadmap for SMEs, as well as considering management views and the function of maturity models in enhancing and structuring data analytics adoption in an organisation. The authors described 14 main problems and obstacles in business analytics and big data analytics in SMEs, as well as a business and big data analytics organisational model for SMEs.

The paper concluded that the SME sector's problems are complex, multifaceted, and cross-cutting across multiple dimensions such as IT, data analytic intelligence, organisational structure, managerial models, capital structure and requirements, consulting, labour market, data security, and legal issues. Also covered was the TQM model.

TQM is useful in determining how to aid SMEs, according to researchers. SMEs, on the other hand, expand their big data capabilities, allowing them to continue to be the engines of European industrial and commercial success.

2.3.28 A Big Data Analytics Framework - To Bridge a Gap Between Practitioner and Academic Research

Gloria Phillips-Wren, Lakshmi S. Iyer, Uday Kulkarni, and Thilini Ariyachandra (2015)[45].

The study builds on academic and business talks from the BI Congress III workshop in 2012 and the Special Interest Group on Decision Support Systems (SIGDSS) session in 2013. The study's goal was to bridge the gap between academic and practitioner research by proposing a big data analytics framework that displays a process view of the components required for big data analytics in businesses. The study incorporated both primary and secondary data. Interviews with practitioners were conducted, and secondary data was gathered from a variety of sources. The framework for big data analytics is also provided by the authors.

The study's authors discovered that the constraints posed by big data's nature provide distinct chances for research in each component of the big data analytics framework.

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[45]**Gloria Phillips-Wren, Lakshmi S. Iyer, Uday Kulkarni, and Thilini Ariyachandra (2015),** Business Analytics in the Context of Big Data: A Roadmap for Research, courtesy of Association for Information Systems: http://aisel.aisnet.org/cais/vol37/iss1/23/

2.3.29 Use of Big Data for the Growth of SMEs

Ogbuokiri, B.O, Udanor C.N., Agu, M.N. (2015)[46], The purpose of this study is to determine the extent to which Big Data can be used for SME growth and to develop a systems-based strategy for making Big Data-based interventions for SME growth. The authors looked at a variety of studies on SMEs and big data implementation for regional growth, as well as the characteristics and importance of big data solutions in SMEs. The authors looked at several big data analytics that can help SMEs grow in their regions. Small and medium-sized firms (SMEs) can profit from using big data and applying it to their analytical practises, according to the report.

According to the findings, SMEs should recognise the basic potential of Big Data for better decision-making and policy formulation in markets and business models, and begin to investigate the possibilities.

Duan, Yanqing, Cao, Guangming (2015)[47].

The primary data was obtained from 296 respondents from UK businesses, indicating that the study model gives a targeted and validated view on the contribution and innovation of business analytics. On the basis of survey data, the hypotheses were empirically tested using partial least squares structural equation modelling (PLS-SEM).

BA contributes to new product meaningfulness (NPM) through improved environmental scanning (ES), but not through the mediation of data-driven culture (DDC), according to the report. The model testing findings also show that many other aspects can influence innovation success, which should be addressed in addition to the BA applications.

According to the results of the model testing, the success of innovation can be influenced by a variety of additional aspects that need be addressed in addition to the BA applications.

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[46]**Ogbuokiri, B.O, Udanor C.N., Agu, M.N. (2015),** Implementing bigdata analytics for small and medium enterprise (SME) regional growth, IOSR Journal of Computer Engineering (IOSR-JCE), p-ISSN: 2278-8727, Volume 17, Issue 6, Ver. IV

[47]**Duan, Yanqing, Cao, Guangming (2015),** AN ANALYSIS OF THE IMPACT OF BUSINESS ANALYTICS ON INNOVATION, Conference: 23rd European Conference on Information Systems (ECIS 2015) At: Münster

2.3.30 Whether Big Data is Necessary for Huge Corporation as Well as for Small Enterprises

Cukier (2014)[48] Big Data, it's been suggested, is better data. Big Data isn't necessary for SMEs, according to Campbell Williams, marketing director of Six Degrees Group. However, not everyone shares this viewpoint. Leaders in Big Data and Analytics, such as Lauren Walker of IBM UK & Ireland, believe that SMEs should use Big Data to obtain a competitive advantage and flourish. This can be accomplished by studying their previous performance and integrating it with external data to predict market behaviour and unearth fresh insights.

According to the findings of this study, while some authors reject the importance of big data for SMEs, the majority of individuals believe that big data is utilised to gain competitive knowledge and growth by analysing historical performance and market behaviour.

Jones (2014)[49], Big data, according to this author, refers to data sets that are too massive and complicated for enterprises to manage using typical IT systems, regardless of their size. However, once you get past the technical lingo, you'll see that big data is all about opportunity. The ability to get knowledge from a company's data in order to make more informed business decisions. While it is unsurprising that huge corporations are taking advantage of the opportunities presented by big data, some entrepreneurs may be unaware that small enterprises can do the same. Big data, on the other hand, is altering the business landscape. There's a good chance that some of your competitors, big and small, are leveraging big data to improve product quality, marketing operations, and customer connections.

Larger competitors' improved efficiency can pose a serious danger to the long-term viability of small businesses. With big data now on everyone's mind, new solutions are being introduced on a daily basis, some of which are tailored to the needs of small enterprises.

This research aided researchers in comprehending enormous data sets utilised by large and complicated businesses to improve product quality, make better business decisions, improve marketing operations, and strengthen customer relationships. Initially, huge corporations

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[48]**Cukier, K., (2014)** Big Data is Better Data. Available at: https://www.ted.com/talks/kenneth_cukier_big_data_is_better_data/transcript?language=en.

[49]**Southard jones (2014)** Retrieved fromhttp://www.entrepreneur.com/article/235338

believed that it would be too costly and difficult to deploy for SMEs, but some small and medium-sized business owners are focused on fast identifying the right solution for the right people.

Donna M. Schaeffer, Patrick C. Olson (2014)[50], The research looked at how small and medium-sized businesses can handle massive amounts of data, or "Big" data. The authors offered information regarding small businesses and information technology, as well as the dimensions of big data, in the study, which was based on secondary data.

The study found that cloud is the best alternative, and it took into account not just the volume of data, but also the variety of data kinds, the speed with which data is created and sent, and the relevance of data veracity.

Nada Elgendy and Ahmed Elragal (2014)[51].

The article looked at some of the numerous analytics methodologies and tools that may be used with big data, as well as the potential that big data analytics can give in diverse decision domains. The authors offered a brief overview of big data analytics and decision making in the study, including customer intelligence, supply chain and performance management, quality management and improvement, risk management, and fraud detection. MapReduce and HDFS were used to explain data analytic processing.

According to the study, significant information may be retrieved and used from big data using such analytics to improve decision making and support informed decisions. Big data analytics may open up a world of possibilities in a variety of applications and domains, and its advantages can benefit a variety of sectors and businesses, including healthcare, retail, telecom, manufacturing, and so on.

Vikas Dhawan and Nadir Zanini (2014)[52], The article covered an overview of big data as well

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[50]**Donna M. Schaeffer, Patrick C. Olson (2014),** Big Data Options For Small And Medium Enterprises, Review of Business Information Systems, Volume 18, Number 1

[51]**Nada Elgendy and Ahmed Elragal (2014),** Big Data Analytics: A Literature Review Paper, Conference Paper, Lecture Notes in Computer Science, t: https://www.researchgate.net/publication/264555968

[52]**Vikas Dhawan and Nadir Zanini (2014),** Big data and social media analytics: A Cambridge Assessment publication. http://www.cambridgeassessment.org.uk/research-matters/

as some of its uses in a variety of disciplines, including education. The authors also discussed the use of big data for market expansion and brand management by monitoring social media (such as LinkedIn, Facebook, and Twitter). The article discusses some big data training courses given by various colleges.

According to the findings, schools and educational institutions have vast volumes of data about pupils. In summative or diagnostic evaluations, this could contain biographical information (such as socioeconomic status and ethnicity) and performance history (marks/grades/teacher observations). Computer-based assessments, for example, allow for the collection and analysis of more data sources.

Thompson et al. (2013)[53] reveals that there is a widespread assumption that a focus on innovation will help SMEs develop faster. One of the factors of competitive advantage is the firm's ability to create information from a new technology, such as the usage of big data. Given this, technology leadership, new process R&D, and creativity can all contribute to innovation. As a result, SMEs must take business risks and should not be frightened of failure in order to progress in the future.

The researcher concludes that SMEs are growing due to their ability to generate information from new technology such as data analytics and its benefits. It provides qualities such as technical leadership, innovative process R&D, and creativity that aid in innovation, allowing SMEs to take business risks while still being prepared for developments.

2.3.31 The Adoption of Big Data Technologies and Techniques Influenced Due to Cloud Solution Providers

Vance (2011)[54], suggested that lower storage prices and widespread availability of cloud solutions from well-known providers like as Amazon, Google, and Microsoft have influenced the adoption of Big Data technologies and techniques positively. Some open-source

[53]T**hompson, P., Williams, R. & Thomas, B., (2013**) Are UK SMEs with active web sites more likely to achieve both innovation and growth? Journal of Small Business and Enterprise Development, 20(4), pp.934–965.

[54]**Vance, A. (2011).** The data knows. Bloomberg Business week, pp. 70–74

technologies, including as Hadoop, have begun to be setup as standards for storing and analysing massive and diverse datasets in this context.

This research assisted researchers in understanding that because data is a competitive advantage, a wide range of cloud solutions such as Amazon, Google, and Microsoft have embraced Big Data technology, with Hadoop as an open source solution being utilised for standards and datasets.

John Ackah and Sylvester Vuvor (2011)[55], The purpose of this study, Small and Medium Enterprises' Challenges in Obtaining Credit in Ghana, was to emphasise the difficulties that SMEs in Ghana encounter in obtaining bank credit (loans) from financial institutions (banks and non-banks) to carry out various activities. The quantitative method was used. Questionnaires were sent to 80 SMEs in Accra and Tema, which were chosen using a convenience sampling technique.

The study concluded with some recommendations to help the SME sector gain access to cash or credit. Encouragement of financial institutions (banks and nonbanks) to develop factoring services, implementation of the credit reporting act, and finally, tax incentives for banks that lend to SMEs to encourage others to do the same are among the ideas.

Asta and Zaneta(2010)[56]The growing importance of small and medium firms (SMEs) and their impact on Lithuania's economic development necessitates paying close attention to their operations, trends, and prospects, as well as encouraging the search for effective SME performance improvement strategies. They stated that in order to increase their environmental, economic, and social effectiveness, they need an integrated, financial-based decision-making model that is geared toward strategic sustainability goals and does not need a substantial amount of time, money, or human resources. The foundation of a sustainable development decision-making model for SMEs is the integration of sustainability management accounting (SMA) and composite sustainable development index (ICSD) approaches.

The researcher gains a better understanding of the expanding relevance of SMEs, their impact

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[55]**John Ackah and Sylvester Vuvor (2011),** The Challenges faced by Small & Medium Enterprises (SMEs) in Obtaining Credit in Ghana, School of Management

[56]**Asta, L. &Zaneta, S. (2010).** Sustainable development decision-making model for small and medium enterprises. Environmental Research, Engineering and Management. 2(52), 14-24

on economic development, and how SMEs perform well in improvement metrics as a result of this research. It also assists SMEs with financial analysis, decision-making models, and financial and human resources for long-term growth.

Ogunsiji and Ladamu (2010)[57]

Entrepreneurial orientation, it is believed, is the remedy for dwindling productivity. Each of these growth engines, such as people, market, money, technology, and organisation, can only completely bloom and flower where the value of entrepreneurial orientation is recognised and executed for small and medium businesses.

This research assisted researchers in understanding entrepreneurial orientation as a universal productivity solution, as well as how it is valued and implemented in small and medium businesses.

Lawal, et al (2010)[58]He claims that there is no uniform definition of small-scale industry based on his findings. Definitions alter over time as a result of pricing changes, technological advancements, and other factors. Turnover, gross output, and employment are frequently utilised in the definition of small-scale businesses (SSEs). These variables are frequently employed because they are practical and straightforward to quantify. SME is a useful phrase for segmenting firms and other organisations that are midway between the "small office-home office" (SOHO) size and the bigger company, according to Rouse (2011). An SME is defined by the European Union as a legally separate firm with less than 500 employees.

The researcher appreciates several types of definitions of SMEs as organisations and also describes how SMEs range from diverse marketplaces from urban to international level by having various levels of skills, capital, sophistication, and growth orientation by having formal economy.

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[57]**Ogunsiji, S. O. and Ladanu, W. K. (2010).** Entrepreneurial orientation as a panacea for the ebbing productivity in Nigerian small and medium enterprises: A theoretical perspective. International Business Research, 3 (4), 192-199.

[58]**Lawal, A. A.And Bello, M.A. (2010)** Business Policy and Strategic Management. Lagos. Suhanif Nigerian Enterprises

2.3.32 Various Factors Related to Contribution of SMEs to an Economy

Oluba (2009)[59] Greater utilisation of raw materials, employment generation, encourage rural development, development of entrepreneurship, mobilisation of local savings, linkages with larger industries, provision of regional balance by spreading investments more evenly, provision of avenue for self-employment, and provision of opportunity for training managers and semi-skilled workers are some of the contributions of SMEs to an economy, particularly in developing countries.

This research assisted researchers in learning about the contribution of SMEs to an economy through several variables such as the utilisation of raw materials, the creation of jobs, the encouragement of rural development through mobilisation, and the opportunity to train managers and workers.

Guangming Cao, Yanqing Duan, Gendao Li (2004)[60], This article created a research model that connects corporate analytics to the effectiveness of organisational decision-making. Structural equation modelling is used to test the research model, which is based on 740 answers from UK enterprises. The major findings showed that business analytics has a beneficial impact on information processing capacities, which in turn has a favourable impact on decision-making effectiveness, thanks to the mediation of a data-driven environment.

According to the findings, there are no statistical variations in the paths from business analytics to decision-making efficacy between large and medium businesses, although there are considerable disparities between manufacturing and professional service industries.

Ayyagariet al (2003)[61]The researcher talked about asset sales and/or value. The number of employees is the most widely utilised variable due to its simplicity of collecting. With a few

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[59]**Oluba N. Martin (2009),** Small and Medium Scale Enterprises and Economic Growth, Pakistan Journal of Business and Economic Review Vol. l. 2, Number 1 (2009).

[60]**Guangming Cao, Yanqing Duan, Gendao Li (2004)**.Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis

[61]**Ayyagari, Meghana and Demirgüç-Kunt, Asli and Beck, Thorsten (2003),** Small and Medium Enterprises across the Globe: A New Database. World Bank Policy Research Working Paper No. 3127. Available at SSRN: http://ssrn.com/abstract=636547

exceptions, such as Japan (300 employees) and the United States, the EU and a large number of OECD, transition, and developing nations set the upper limit of number of employees in SMEs between 200 and 250. (500 employees). A huge number of countries designate a category, which is a combination of self-employed and micro firms with less than 10 employees, at the bottom end of the SME sector.

Regardless of an economy's level of development, the informal sector or shadow economy houses a considerable number of micro and, in certain cases, tiny businesses (OECD, 2002). From 2000 to 2002, the OECD (2004) and Schneider (2003) compared the size of the informal sector in 22 transition (former Soviet Union and Central and Eastern Europe) and 21 OECD economies, finding that the informal sector accounted for an average of 16.7%, 29.2%, and 44.8 percent of GDP in OECD, Central and Eastern European, and former Soviet Union economies, respectively.

The researcher concludes from this study that there are less small businesses in the country, although this is not the case. Small businesses are, in fact, as popular as ever. The drop in self-employment was mostly due to a decrease in the number of independent farmers, which was partially offset by an increase in large business employment.

Priyanka Anand P and Dr Sanjay Banerji (2017)[62], The article looked at the influence Business Analytics (BA) can have on Indian SMEs in terms of performance and correctness of four main areas of SCM, namely Plan, Source, Make, and Deliver, in decision-making attributes so that they can perform better in the market. The analysis is based on observations as well as the findings of expert interviews and an online poll conducted as part of the study. The sample size for the study was around 150 people, all of whom represented SMEs from across India. The study used Structural Equation Modelling (SEM), which establishes the relationship between the dependent and independent variables as well as the moderator influence, i.e., the information system.

With a small investment in information systems, the researcher believes that BA can play a

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[62]**Priyanka Anand P and Dr. Sanjay Banerji (2017),** Analysing the impact business analytics can have on Indian SME’s supply chain performance, Amrita School of Business, Amrita University, Coimbatore, India

major role in enhancing the performance of Indian SMEs. Small businesses can begin with basic BA tasks, and this study found that while SMEs are willing to apply BA approaches in supply chains, they are sluggish to adopt newer technologies and are willing to adopt greater automation and critical learning from information systems.

2.4 Conclusion

This chapter explains that data controlled by big data platforms can come from any source, including the physical and virtual worlds, and that if the data is processed efficiently, the results of collective data analysis will almost surely display a bigger picture that is near to reality. It also summarises how large corporations and small businesses make excellent business decisions. Many writers' discussions of Data Science branches such as Data Analytics, Business Intelligence, Data Mining tools, and Cloud computing techniques for financial and organisational approaches and upgrades for market betterment have also been highlighted through the findings of prior studies.

Various research with a focus on Data Analytics and Information Technology have been highlighted the most. The chapter thus provides a detailed chronological overview of the evolution of Data Analytics and its tools in SMEs, as well as how these businesses are improving their business decisions, by citing the findings of leading research papers on the subject. The majority of the research presented in this chapter was conducted by foreign authors.

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Chapter-3: Research Methodology

3.1 Research Approach

Quantitative research has dominated western culture to generate new knowledge and meaning. A numeric or statistical approach to research design defines a quantitative research method. Quantitative analysis is specific in surveying and experimentation since it builds on existing hypotheses. The premise of an empiricist worldview is maintained throughout the approach of quantitative research. The research is self-contained and unaffected by the researcher's actions. As a result, data is utilised to measure reality objectively. The quantitative analysis gives significance to the information it collects by revealing objectivity.

Quantitative research can answer questions about the relationships between variables in a study. Quantitative researchers are looking for explanations and forecasts that can be applied to other people and locations. The goal is to "create generalisations that add to the theory". Quantitative research starts with a problem description and includes developing a hypothesis, doing a literature study, and analysing quantitative data. The quantitative analysis employs inquiry methodologies such as experiments and surveys and collects data on specified instruments that provide statistical information. Quantitative research findings can be predictive, explanatory, and confirmatory.

3.2 Research Background

According to research released today, India's business analytics software market is expected to increase at 9.6% year on year through 2019, reaching $583 million (approximately Rs. 3,442 crores), compared to 6.8% in the Asia-Pacific region[1].

Organisations are treading carefully when it comes to implementing analytics. The use of business analytics in firms has increased slowly, although slowly. Analytics is also frequently employed only inside departments or business divisions rather than integrated throughout the firm. The field of business analytics is still in its infancy. Even though business analytics has become main stream, most businesses still rely on out dated technologies.

The micro, small, and medium-sized enterprise (MSME) sector is critical to India's economic growth. More than 94 per cent of the units are unregistered, indicating that the industry is substantially disorganised. In the areas of lending, technical advancement, marketing, and entrepreneurship development, the government has created a variety of measures to help the MSME sector grow. Even though the industry has been growing in terms of the number of MSME units, fixed asset investment, and job creation, several issues have resulted in different inefficiencies of the units at various decision-making stages.

The current requirement of the hour for this industry is to familiarise oneself with data-driven information technology and use it to develop and expand businesses.
Because they do not perceive the value of investing in business analytics tools, most MSME firm owners make decisions based on best guesses or their business environment perceptions. The ability to acquire and analyse information quickly and accurately is crucial for the MSME to function in a highly competitive environment.

Business analytics (BA) tools are equally useful for small and large businesses. Companies may use the solutions to secure information integrity, enhance decision-making, and improve corporate performance.

Whether the economy is in a downturn or boom, the MSME must efficiently combine data from several sources and consolidate it to draw relevant insights and change the business. Finally, successful use of analytics will mark a well-managed MSME, demonstrating that it is an organisation that can always effectively address critical business concerns, assuring prompt, accurate, and informed business choices.

3.3 Identified Research Gap

The following research gaps in the context of the current study have been discovered through review of previous literature.

- Because of the cost and complexity, most SMEs have not participated in a data analytics study.
- Previous research has not looked into how Data Analytics is used in SMEs to make business choices.
- Other researchers have not taken into account how many SMEs are impacted by the usage of Data Analytics for business choices, which the researcher has addressed in the current study.

3.4 Research Objectives

The Research Objectives of this study are given below:

1. To understand which type of data analytics software companies use.
2. To understand which business functions are using the data analytics tools.
3. To explore which analytics companies, use, to make their decision-making.
4. To study which areas are there, companies are studying using data analytics tools.
5. At which the companies are using business-level data analytics tools.
6. To study whether companies capture the data points as per their business needs.
7. To understand which areas, benefit from using data analytics tools for the companies.
8. To study whether the SME owners/managers are aware of the factors that can inhibit the adoption or implementation of data analytical tools.

3.5 Research Questions

The research questions have been formed to test the several hypotheses, and these questions have been mentioned below:

1. Does the organisation’s usage of open-source vs licensed software depend upon the type of business they are into?
2. Does the usage of a particular analytics service change due to the organisation's number of years of existence?
3. Is there any correlation between the decision-making levels using data analytical tools?
4. Are the data capturing points related to the organisation’s business need?
5. Are there any correlations between the value of data analytics tools or services and the inhibitors perceived by the organisations?

3.6 Research Hypothesis

Hypothesis-1

H0: There is no association between the type of business and ownership of data management software by SME companies.

H1: There is an association between the type of business and ownership of data management software by SME companies.

Hypothesis-2

H0: There is no association between the age of the SME company and the usage of particular data analytics service.

H1: There is an association between the age of the SME company and the usage of particular data analytics service.

Hypothesis-3

H0: There is no correlation between decision-making components that uses data analytics tools in SMEs.

H1: There is a correlation between decision-making components that uses data analytics tools in SMEs.

Hypothesis-4

H0: There is no association between the data elements considered per business needs and data preparation in SMEs.

H1: There is an association between SMEs' data elements considered as per business needs and data preparation.

Hypothesis-5

H0: There is no correlation between the understanding of data analytics tools and the clarity about the inhibitions which can hamper the usage of data analytics tools amongst SMEs.

H1: There is a correlation between the understanding of data analytics tools and the clarity about the inhibitions which can hamper the usage of data analytics tools amongst SMEs.

3.7 Research Process

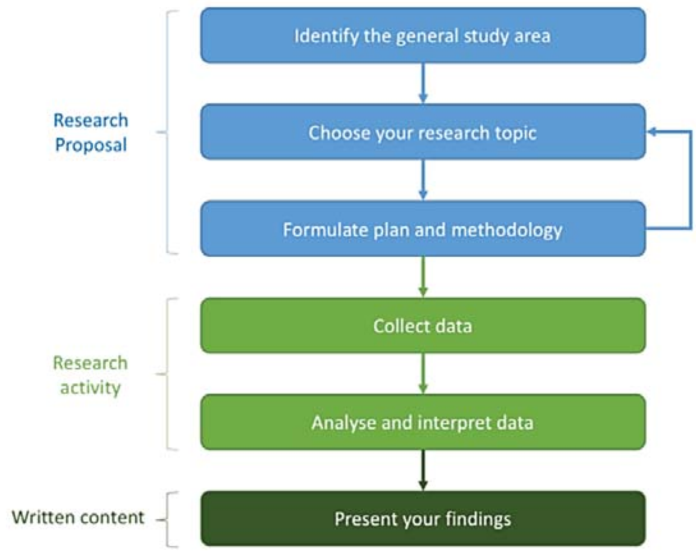

Figure 8: Research Process

3.8 Parameters / Variables / Constructs considered

a) Purpose Of Analytical Tool Usage in Fun
b) Type Of Analytics Used for Decision Marketing
c) Data Analytical Tool Is Helpful for Your Enterprise
d) Usage Of Data Analytical Tools in Your Organization Based On Decision-Making Categories
e) The Utility of Data Analytics Tools
f) Analytics forms business perspective
g) Demographic variables

3.9 Method of Data Collection

A cross-sectional approach was used in this study's data collection. Cross-sectional research is preferred because it adequately represents the respondents' experiences, views, and beliefs at one point in time. It is possible to generalise the results obtained from a small sample of people to a larger group using a questionnaire technique. The researcher has used the google forms to collect the required information for the research study.

3.10 Structure of Questionnaire

The structured questionnaire included demographic questions and questions using a Likert scale, according to the researcher. The questionnaire is divided into two parts. The questionnaire is focused on identifying the usage of analytics in the SME industry.

Questionnaires were created to get feedback on a variety of quantitative characteristics. Google forms were used to collect the information for Survey Instrument. Aspects of assurance relating to data confidentiality were clearly stated at the outset of the online questionnaire.

The questionnaire stated that this data would only be used for academic study and would not be shared for any other purpose. This provision was intended to decrease respondents' anxiety while maintaining the confidentiality of research data.

Following the study aims and hypotheses derived, this questionnaire is appropriate. It is easy to study the descriptive connection because it includes questions about company-related demographic data. With simple wording and largely positive connotations, the questions were framed. In addition, great attention was paid to the length of the questions and the clarity of the replies they elicited.

The questionnaire assisted in the collection of nominal and ordinal data. A Likert Scale was used to get ordinal data on the target group's attitudes, while closed-ended questions were used to gather little data, which was primarily demographic.

3.11 Sample Size & Sampling Technique Used

This study primarily focuses on the SMEs explicitly looking at using Data Analytics Tools. This research aims to find out how small and medium-sized businesses (SMEs) view data analytics technologies as beneficial to their operations.

The researcher used Pune's DIC data to establish a sampling frame that included all of the targeted population's (Pune's SME owner/managers) participants. Consequently, the Sample Design was created and described in detail below for this investigation.

The researcher employed Probability Sampling, that to simple random sampling to get a sample from the intended population for the study. The researcher decided to survey Pune based on this plan. Pune is home to a large number of small and medium-sized businesses. Because of the following factors, Pune was chosen as a representative sample of SMEs.

The sampling unit in this research study is the owner/manager of the SMEs in Pune, whereas the sampling units are those who are using data analytical tools in their day-to-day business practices.

3.12 Target Population and Sample Size

The population is unknown in this case as the SME sector is unorganised, and the district industries centre has mentioned the same in their respective annual reports year on year.
Hence considering the unknown population, the researcher has regarded the following formula to calculate the sample size:

Unlimited population:

$$CI = \hat{p} \pm z \times \sqrt{\frac{p(1-p)}{n}}$$

Sample size: **385**

This means 385 or more measurements/surveys are needed to have a confidence level of 95% that the real value is within ±5% of the measured/surveyed value.

Confidence Level:	95%	
Margin of Error:	5%	
Population Proportion:	50%	Use 50% if not sure
Population Size:		Leave blank if unlimited population size.

3.13 Pilot Study

The researcher has conducted a pilot survey with 40 respondents. While carrying out the pilot survey, the researcher has found that the survey instrument is easily understandable to the respondents. The clarity of the questions is very much visible to the respondents. No questions have been dropped to the lack of internal consistency, discussed in the next section.

3.14 Reliability & Validity test

3.14.1 Reliability Test

A Cronbach's alpha test can determine the consistency of the items being measured to determine a questionnaire's reliability. To be judged "substantially acceptable," the test outputs a value from zero to one. Higher than 0.8 scores are deemed highly satisfactory, while lower than 0.6% are considered unacceptable. As a result, dependability increases as the score gets closer to 1. Sixty items were used to test the reliability, which left us with reliability of 0.893. It is considered extremely good for the research.

3.14.2 Content Validity

In this research, attention was paid to the constructs, the scaling techniques, and the samples to ensure the results' validity. An evaluation of the scale's capacity to accurately measure what it is designed to measure.

3.15 Statistical Tools Used

The researcher used SPSS 22 to analyse the data. While testing the data researcher had to stick to the following statistical tools and techniques:

a) Descriptive statistics
b) Chi-square test
c) Spearman Rank Correlation test
d) Pearson correlation test

3.16 Timeline of Research

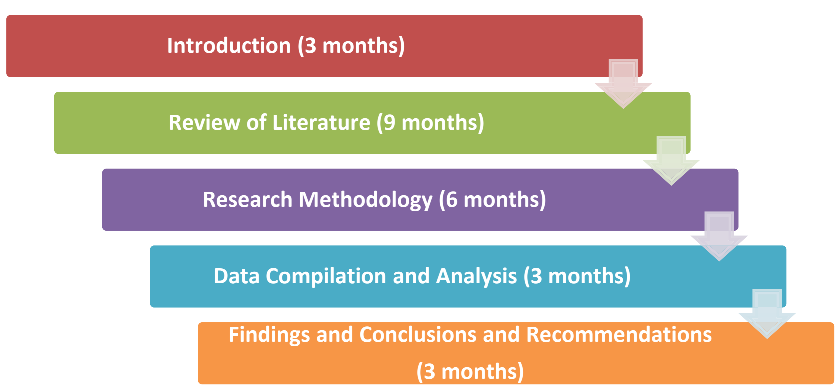

Figure 9: Timeline of Research

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Chapter-4: Data Analysis and Interpretation

4.1 Introduction:

After reviewing the data, this chapter provides an outline of how to accomplish the study's goals. Description and inference of outcomes are discussed extensively throughout the chapter. Graphic and tabular representations are used to convey the findings.

4.2 Demographic Analysis

1) Type of business

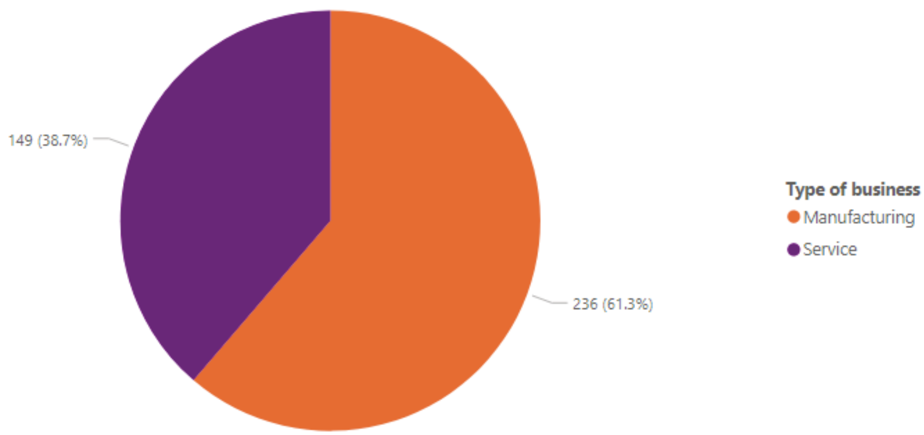

Figure 10: Type of Business

Types of business	Count
Manufacturing	236
Service	149

Table 1:Type of business

Finding: Looking at the above graph we can see that the sample respondents from the manufacturing business were more as compared to the service business who have participated in this academic survey. Almost 61% of sample respondents were from manufacturing while the rest are from the service sector.

2) Time Since Establishment of Organization

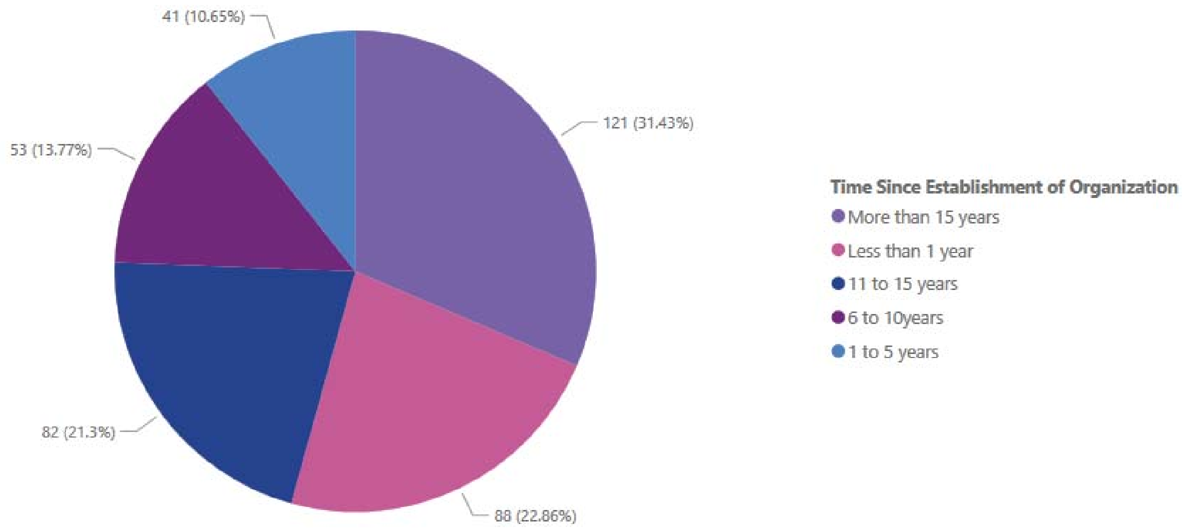

Figure 11: Time Since Establishment of Organization

Time	Count
Less than 1 year	88
"1 to 5 years"	41
"6 to 10years"	53
"11 to 15 years"	82
"More than 15 years"	121

Table 2: Time Since Establishment of Organization

Finding: From the above graph and the table it is evident that the sample organizations which have been considered as a sample unit in this research show that more mature organizations have participated in the survey like who are having their existence for more than 10 years followed by the young organizations which have not yet completed the 1 year the number between this one year and 10 year was comparatively less as compared to the mature one including the younger ones. Hence, we can see that mature organizations have participated very well in the survey.

3) Which data management software do you have?

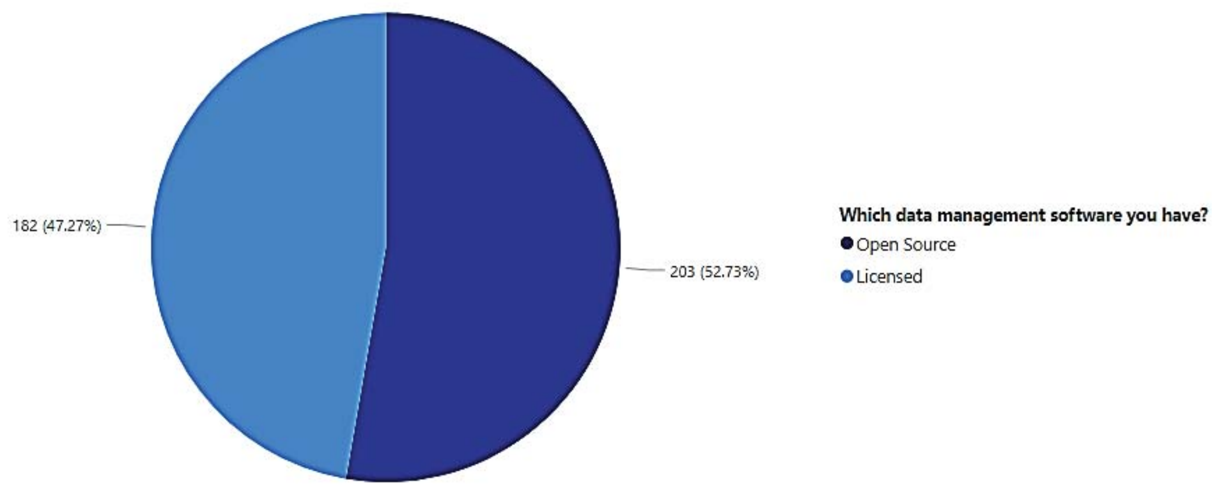

Figure 12: Data Management Software

Software	Count
"Open Source"	203
"Licensed"	182

Table 3: Data Management Software

Finding: As we can see from the above graph that since the study is focused on MSMEs and how they leverage the power of data analytic tools it was quite obvious that maximum MSMEs will be using open-source software as compared to the licensed one we can see that around 53% MSME are using open-source software compared to the licensed ones which are only 47%.

4) Which Data Analytical tools do you use?

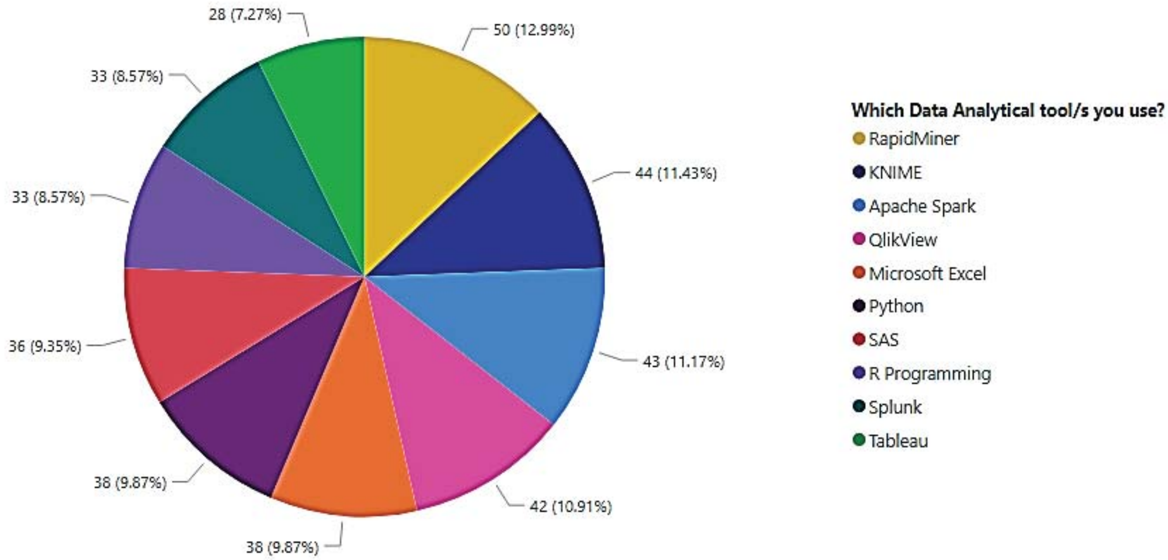

Figure 13: Data Analytical tools

Data Analytical Tools	Count
R Programming	33
Tableau	28
Python	38
SAS	36
Apache Spark	43
Microsoft Excel	38
RapidMiner	50
KNIME	44
QlikView	42
Splunk	33

Table 4: Data Analytical tools

Finding: From the above graph and the table we can see that much of the focus is on data analytic tools which end be used as self-service tools also there are the companies who are giving special attention to the visual analytic tools for their day-to-day business operations.

5) At what extent does your organization use Data Analytical Tool?

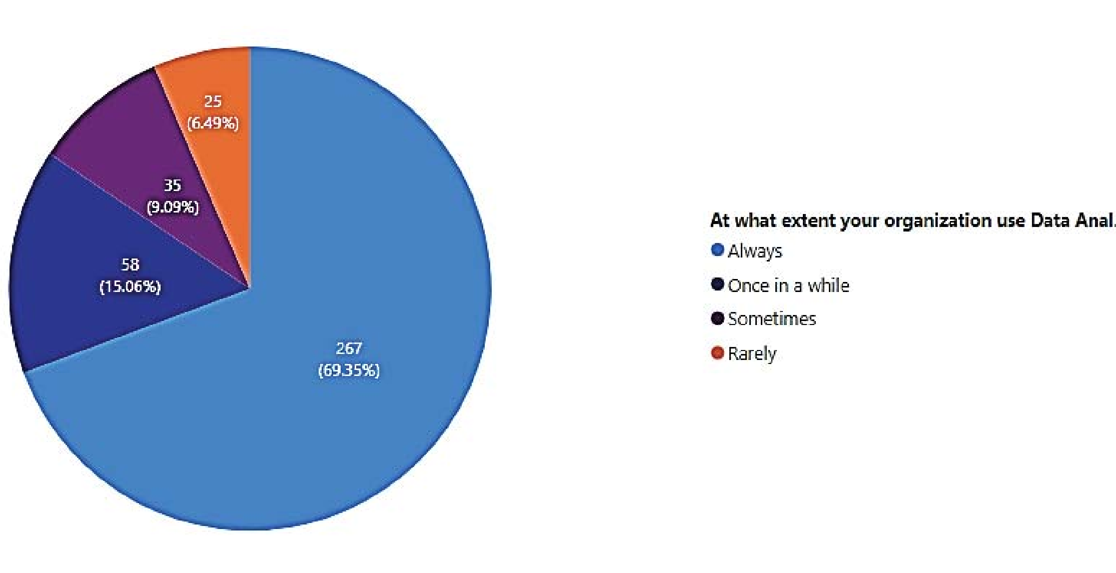

Figure 14: Data Analytical tools use

Data Analytical tools use	Count
Always	267
Sometimes	35
Once in a while	58
Rarely	25

Table 5: Data Analytical tools use

Finding: From the above graph and table we come to know that 70% of the sample organizations are using data analytical tools whereas around 16% of the samples were using it as in when needed that also not too frequently and rest of them are using sometimes. Hence you can see that 70% of the organizations have engrossed data analytics culture in their respective organizations.

6) Purpose of data analytical tool in Sales

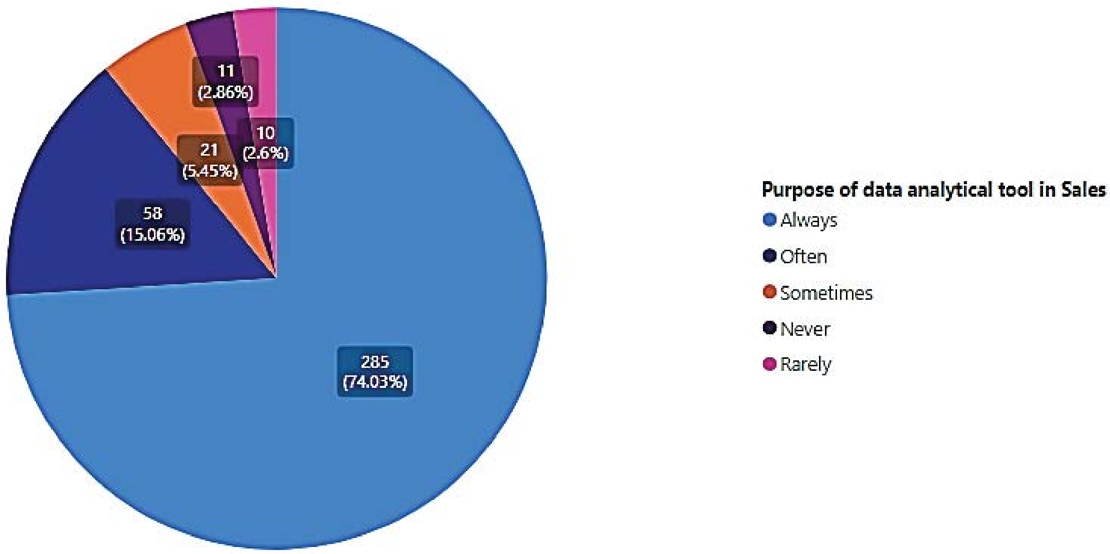

Figure 15:Purpose of data analytical tool in Sales

Purpose of data analytical tool in Sales	Count
Never	11
Rarely	10
Sometimes	21
Often	58
Always	285

Table 6: Purpose of data analytical tool in Sales

Finding: The above graph and table suggest that almost 95% of organizations are using data analytic tools in their sales departments or functions for various purposes such as sales forecasting inventory management and other areas but still 5% of organizations have not adopted the data analytics practice in their sales process.

7) Purpose of data analytical tool in Customer service

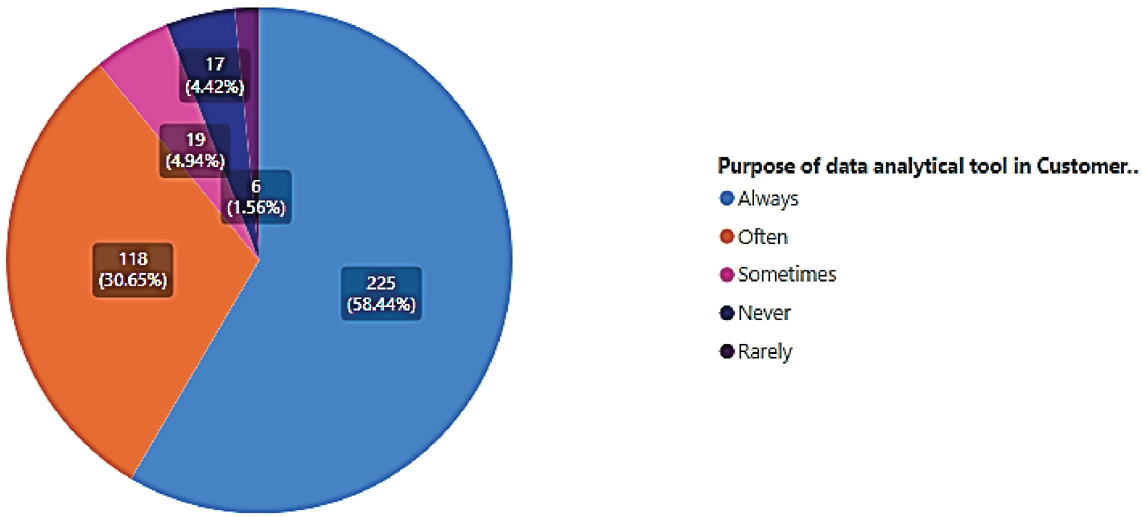

Figure 16: Purpose of data analytical tool in Customer service

Purpose of data analytical tool in Customer service	Count
Never	17
Rarely	6
Sometimes	19
Often	118
Always	225

Table 7: Purpose of data analytical tool in Customer service

Finding: The above table and graph suggest that the other area where the organizations are using data analytic tools is into the management of customer service also we come to know that around 94% of organizations are using data analytic tools in their management of customer journey a customer life cycle which includes understanding their interest inclination towards the product understanding the pain areas of the customers and also how best the organizations can deliver their solutions to delete the customers. 6% of organizations are still not using any sort of analytical service in the management of their customers.

8) Purpose of data analytical tool in Marketing

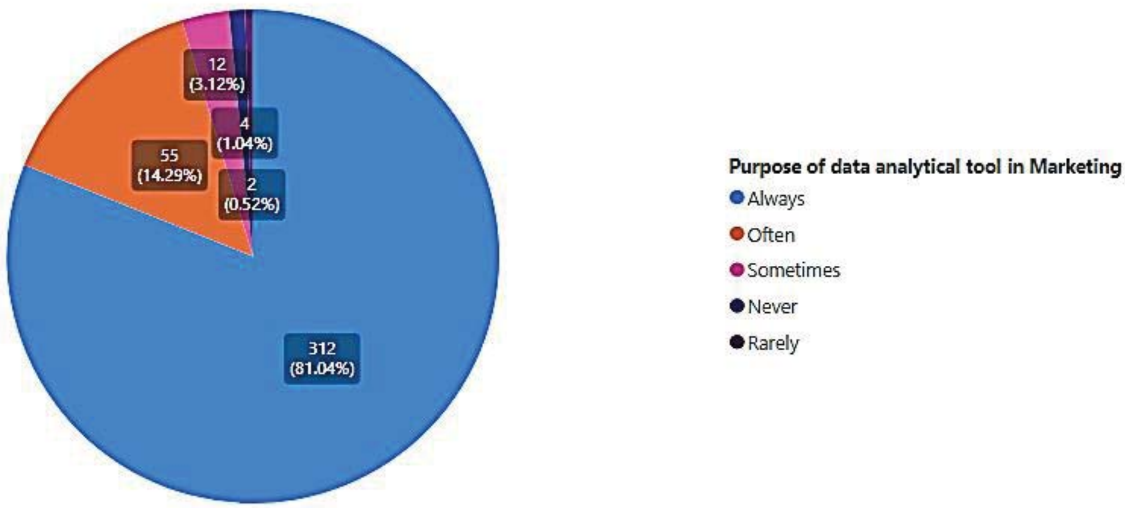

Figure 17: Purpose of data analytical tool in Marketing

Purpose of data analytical tool in Marketing	Count
Never	4
Rarely	2
Sometimes	12
Often	55
Always	312

Table 8: Purpose of data analytical tool in Marketing

Finding: The above graph and table suggest that around 96% of the organizations are using data analytical tools in their marketing functions to manage and understand the impact of various strategies that marketing people are making whereas still 4% of the organisations are lagging or have not adopted the data analytical practice in their marketing functions.

9) Purpose of data analytical tool in Manufacturing

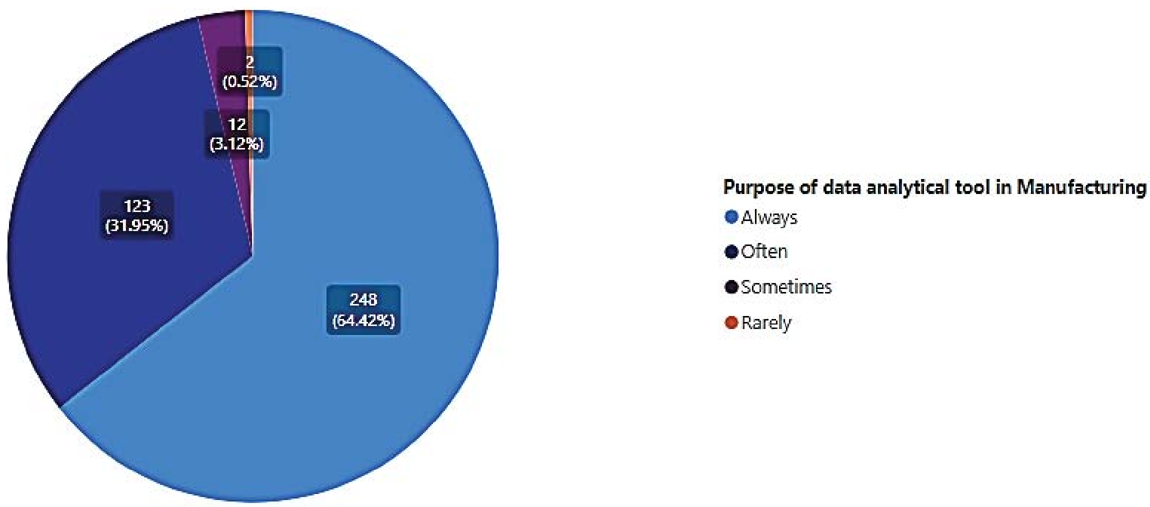

Figure 18:Purpose of data analytical tool in Manufacturing

Purpose of data analytical tool in Manufacturing	Count
Rarely	2
Sometimes	12
Often	123
Always	248

Table 9: Purpose of data analytical tool in Manufacturing

Finding: the above graph end table suggest that around 96% of the organizations are using data analytical tools in their manufacturing functions such as an end-to-end management of raw material or human resource or work in progress and also managing the finished goods whereas still 4% of the organisations her lagging or have not adopted the data analytical practice in their manufacturing functions.

10) Purpose of data analytical tool in Finance

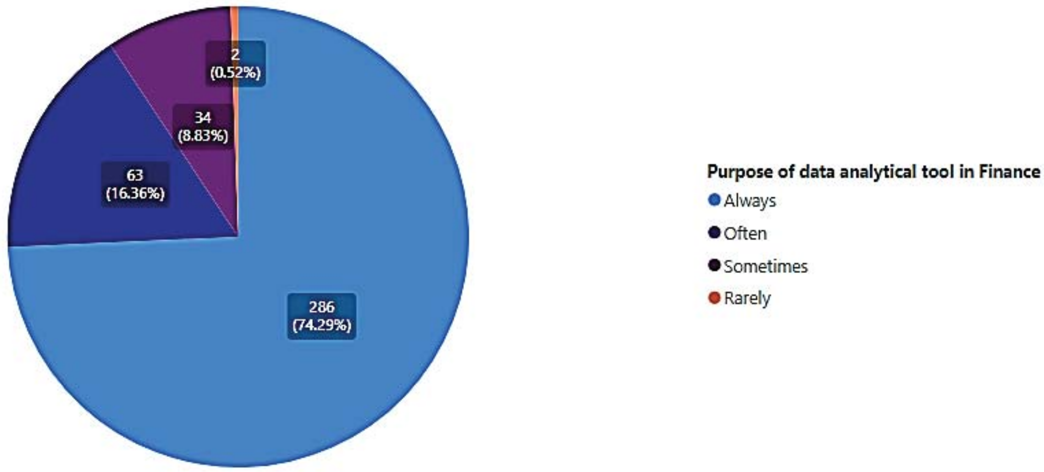

Figure 19: Purpose of data analytical tool in Finance

Purpose of data analytical tool in Finance	**Count**
Rarely	2
Sometimes	34
Often	63
Always	286

Table 10: Purpose of data analytical tool in Finance

Finding: the above graph end table suggest that around 90% of the organizations are using data analytical tools in their finance functions to understand the various head as well as the overheads of the organization which are consuming the financial bandwidth of the organization. But still, there are 10% of the organization who are not using it much or are not in the process of using it for managing their finance function.

11)	Purpose of data analytical tool in Human Resource

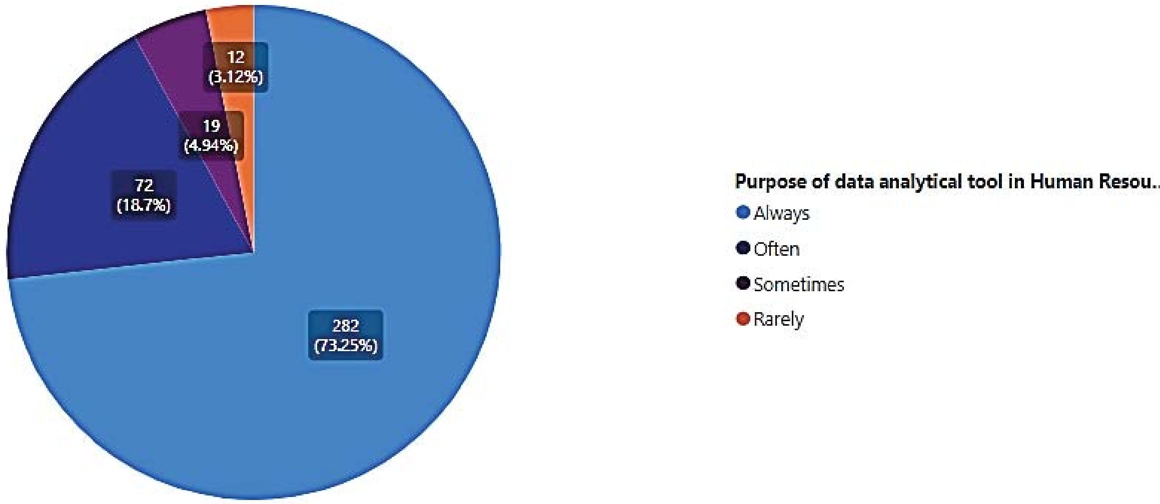

Figure 20: Purpose of data analytical tool in Human Resource

Purpose of data analytical tool in Human Resource	Count
Rarely	12
Sometimes	19
Often	72
Always	282

Table 11: Purpose of data analytical tool in Human Resource

Finding: The above graph and table suggest that around 92% of the organizations are using data analytical tools in their human resource functions to manage and understand the various metrics of human resources such as recruitment, time to fill position, attrition or retention. But still, 8% of the organizations are not leveraging it fully.

12) Purpose of data analytical tool in Risk Management

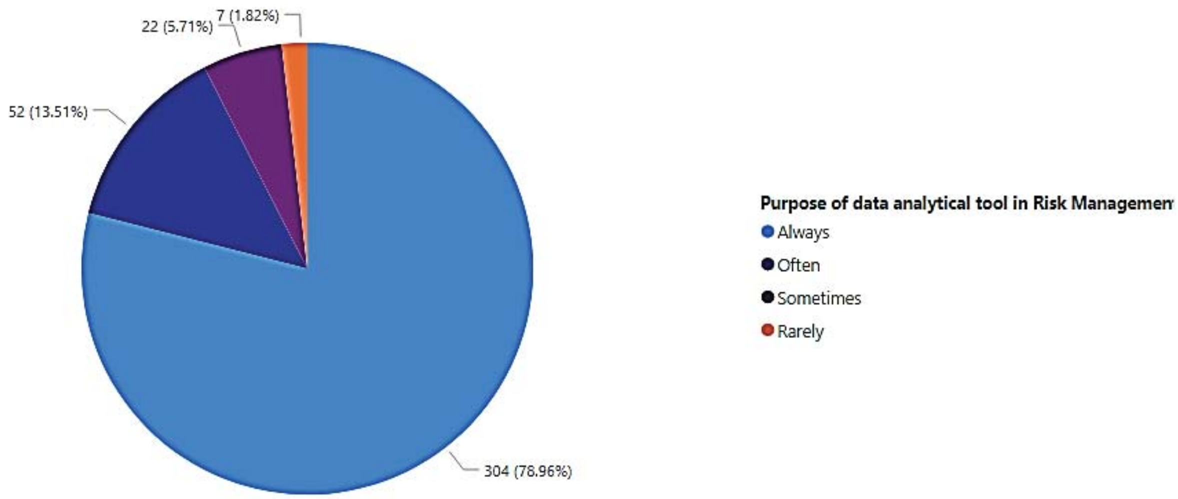

Figure 21: Purpose of data analytical tool in Risk Management

Purpose of data analytical tool in Risk Management	Count
Rarely	7
Sometimes	22
Often	52
Always	304

Table 12: Purpose of data analytical tool in Risk Management

Finding: The above graph and table suggest that around 93% of the organizations are using data analytical tools for managing and mitigating the risk involved in the business. This risk management is very crucial for the organizations since its very important to critically analyze this and these organizations are leveraging this with the help of data analytical tools, whereas human resource functions to manage and understand the various metrics of human resources such as recruitment, time to fill position, attrition or retention. But still, 8% of the organizations are not leveraging it fully.

13) Purpose of data analytical tool in Learning and development

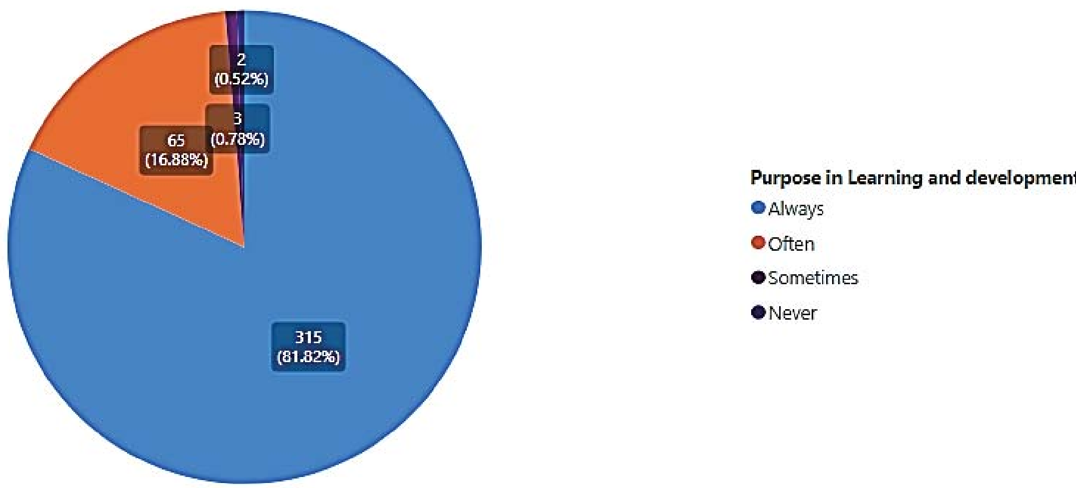

Figure 22:Purpose of data analytical tool in Learning and development

Purpose of data analytical tool in Learning and development	**Count**
Rarely	2
Sometimes	3
Often	65
Always	315

Table 13: Purpose of data analytical tool in Learning and development

Finding: The above graph and table suggest that around 99% of the organizations are using data analytical tools in their learning and development function which is a cost-intensive function since ROI of learning and development function could be understood by analyzing various metrics.

14) Purpose of data analytical tool in Operations

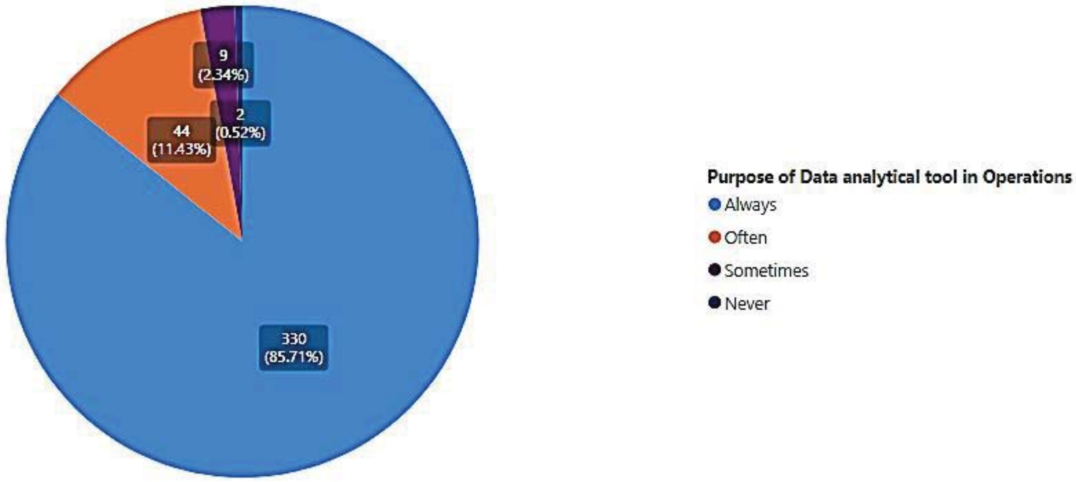

Figure 23: Purpose of data analytical tool in Operations

Purpose of data analytical tool in Operations	Count
Rarely	2
Sometimes	9
Often	44
Always	330

Table 14: Purpose of data analytical tool in Operations

Finding: The above graph and table suggest that around 97% of the organizations are using data analytical tools in their operation management which involves lots of complex activities, managing them and understanding the hidden patterns in those activities is important for any organization to sustain and succeed into the market.

15) Purpose of data analytical tool in other business functions

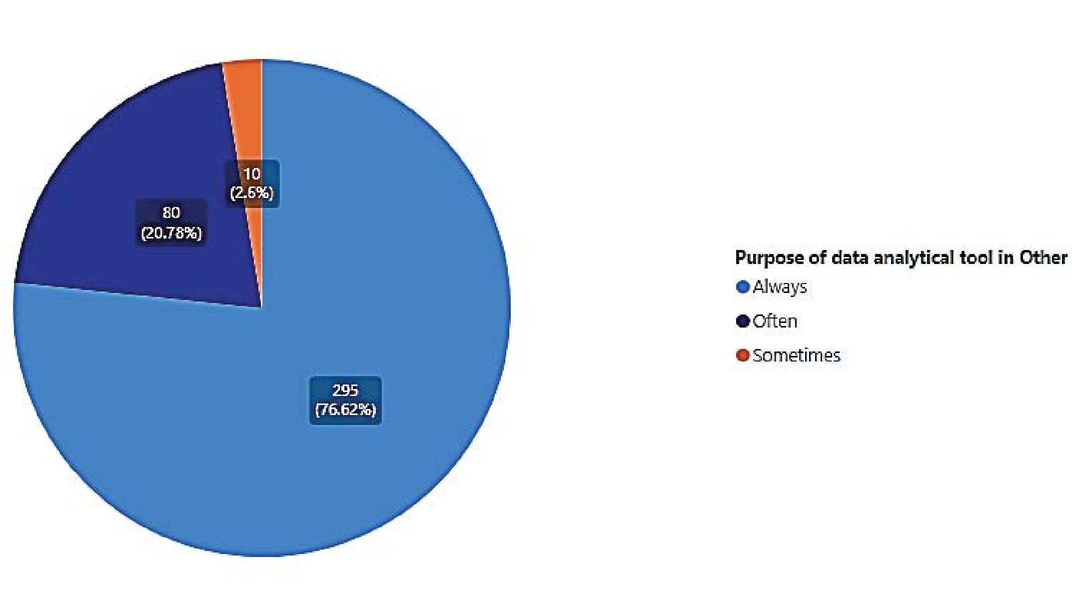

Figure 24: Purpose of data analytical tool in other business functions

Purpose of data analytical tool in Other	Count
Sometimes	10
Often	80
Always	295

Table 4.15: Purpose of data analytical tool in Other

Finding: The above graph and table suggest that around 97% of the organizations are using data analytical tools in different functions other than the functions mentioned above. These functions are having impactful things on other business functions.

16) Which type of Analytics is used for decision-making?

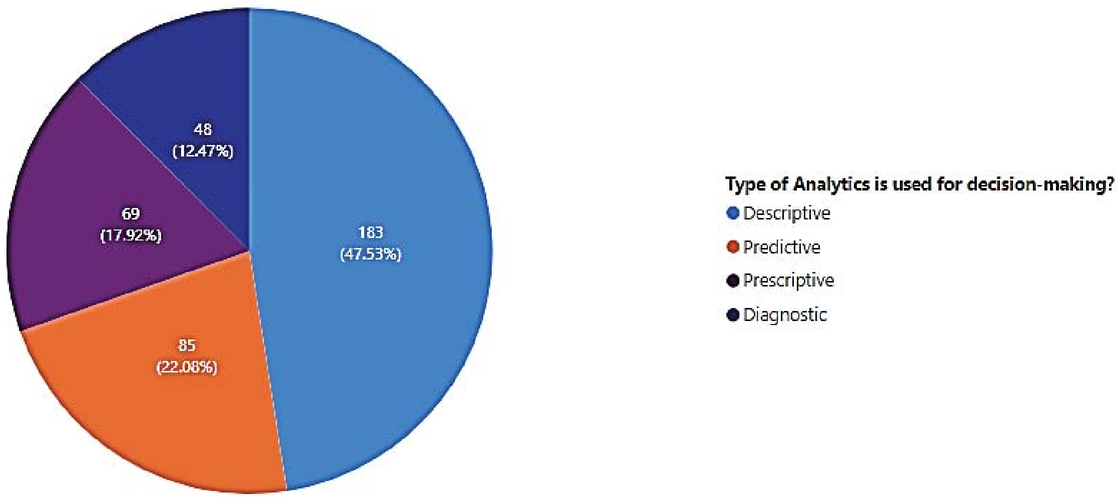

Figure 25: Type of Analytics used for decision-making

Analytics is used for decision-making	Count
Descriptive	183
Predictive	85
Prescriptive	69
Diagnostic	48

Table 16: Analytics is used for decision-making

Finding: The above graph and table suggest that around 48% of the organizations are using descriptive analytics which means these organizations study what has happened based on previous data whereas 22% of organizations are using predictive analytics which means what's going to happen likely. Advanced analytics such as prescriptive or diagnostic analytics are used less by organizations.

17) Data Analytical tool is helpful to understand customer patterns?

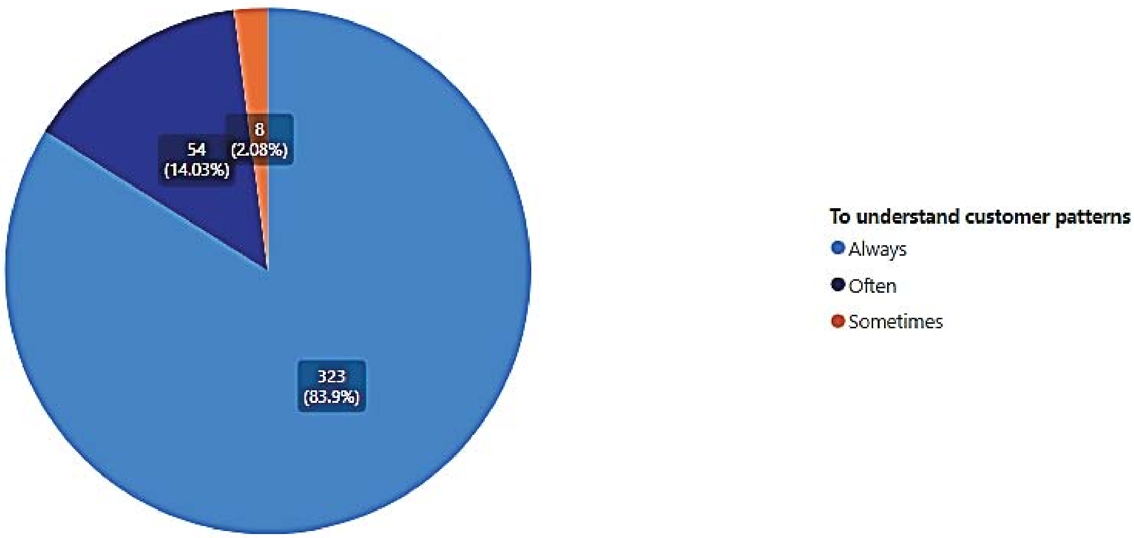

Figure 26: Understanding customer patterns through Data Analytical tool is helpful

To understand customer patterns	Count
Sometimes	8
Often	54
Always	323

Table 17: Understanding customer patterns through Data Analytical tool is helpful

Finding: The above graph and table suggest that around 84 % of the organizations are using data analysis tools to understand the customer patterns always whereas 14% are using this on and off and only 2% of organizations are using sometimes not too frequently which means.

18)	Data Analytical tool is helpful to take Business Decisions?

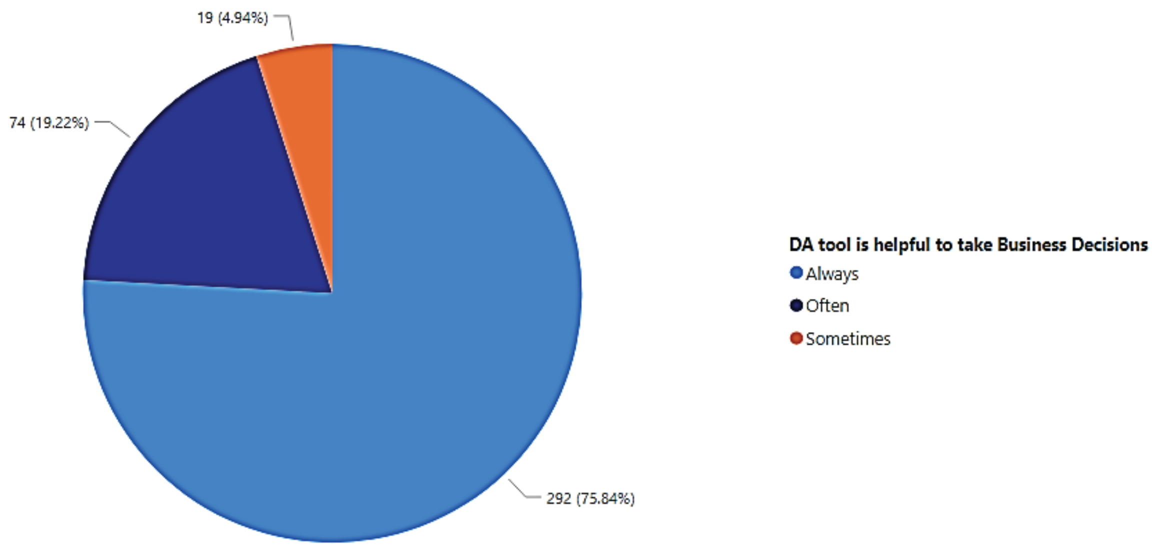

Figure 27: Data Analytical tool is helpful to take Business Decisions

Data Analytical tool is helpful to take Business Decisions	Count
Sometimes	19
Often	74
Always	292

Table 18: Data Analytical tool is helpful to take Business Decisions

Finding: The above graph and table suggest that around 95% of the organizations believe that data analytics tools help them in their business decision quite frequently whereas only 5% of the organizations believe that these tools sometimes only help them in making business decisions.

19) Data Analytical tool is helpful to Managing Relation with Third-party

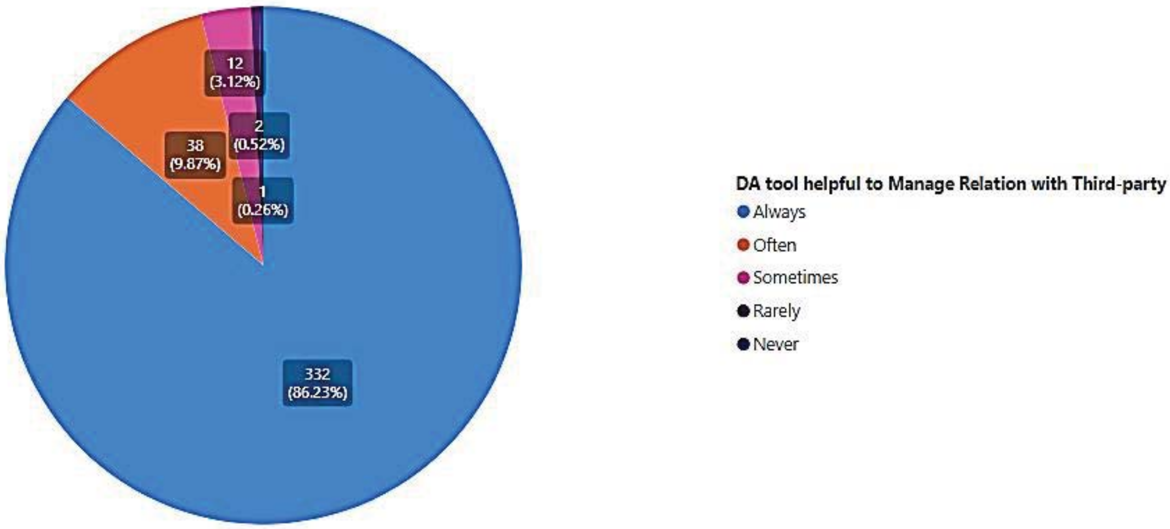

Figure 28: Data Analytical tool is helpful to Managing Relation with Third-party

Data Analytical tool is helpful to Managing Relation with Third-party	Count
Never	1
Rarely	2
Sometimes	12
Often	38
Always	332

Table 19: Data Analytical tool is helpful to Managing Relation with Third-party

Finding: The above graph and table suggest that around 96% of the organizations believe that these data analytics tools help them in understanding the intricacies involved in the relationship management of third-party vendors involved in their business.

20) Data Analytical tool is helpful to gathering information about competitors

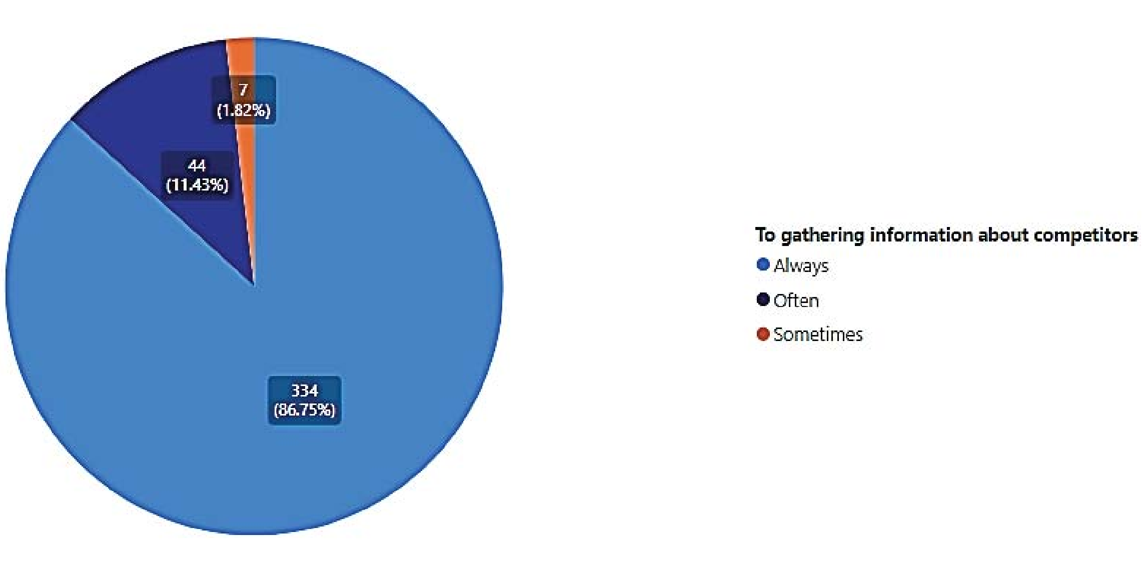

Figure 29: Data Analytical tool is helpful to gathering information about competitors

Data Analytical tool is helpful to gathering information about competitors	**Count**
Rarely	7
Often	44
Always	334

Table 20: Data Analytical tool is helpful to gathering information about competitors

Finding: The above graph and table suggest that around 97% of the organizations are using data analysis tools to capture the data related to the competitor's services and products and understand the pitfalls in their approach based on that which is very useful to the organizations.

21) Data Analytical tool is helpful to Effective Data Management

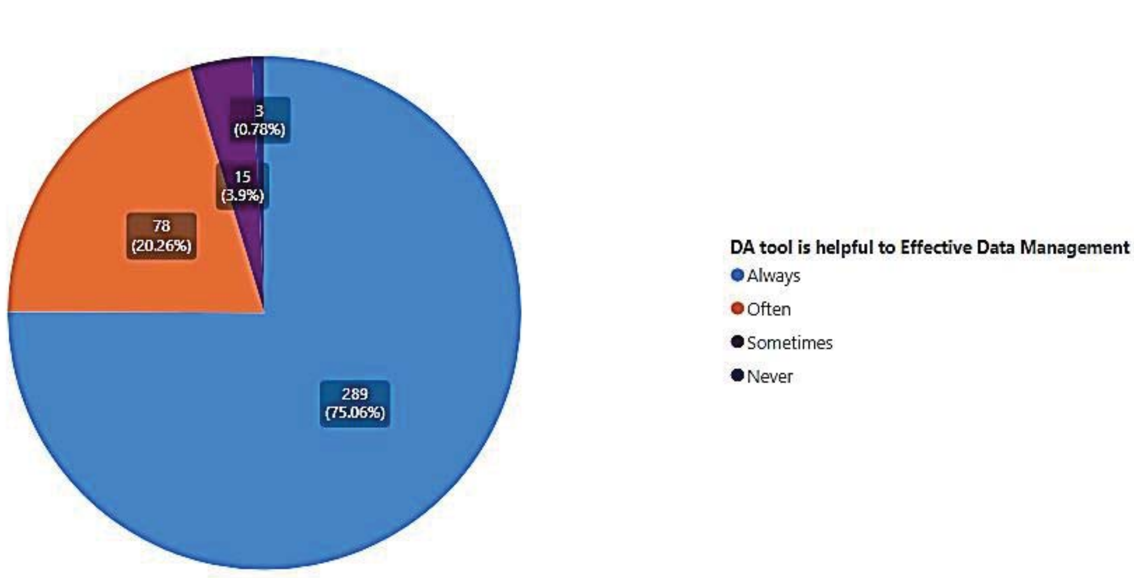

Figure 30: Data Analytical tool is helpful to Effective Data Management

Data Analytical tool is helpful to Effective Data Management	Count
Never	3
Sometimes	15
Often	78
Always	289

Table 21: Data Analytical tool is helpful to Effective Data Management

Finding: The above graph and table suggest that around 95% of the organizations are using data analytics tools to manage their data effectively and efficiently since having structured data helps the analyst to analyse it more properly.

22) Data Analytical tool is helpful to understand business trends

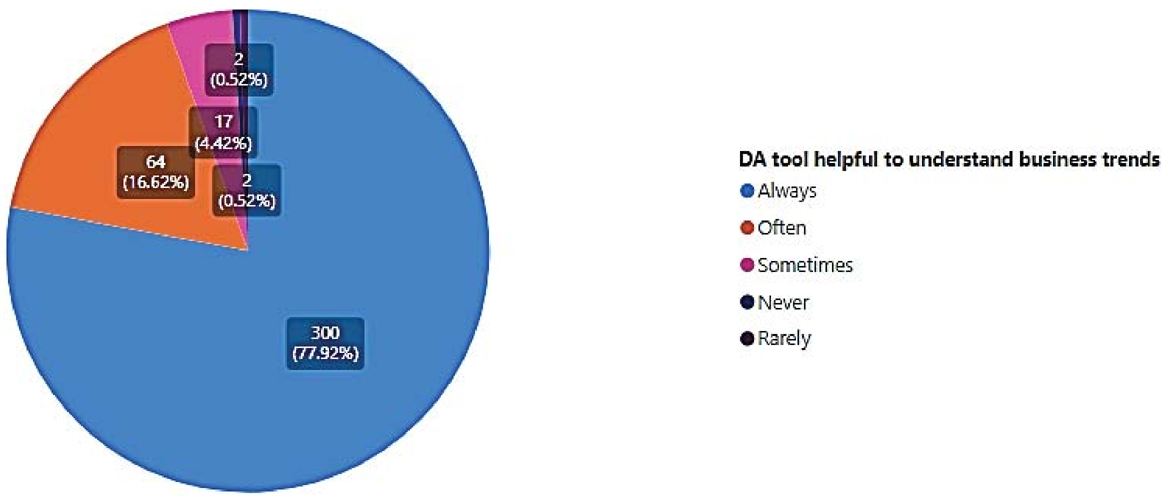

Figure 31:Data Analytical tool is helpful to understand business trends

Data Analytical tool is helpful to understand business trends	Count
Never	2
Rarely	2
Sometimes	17
Often	64
Always	300

Table 22: Data Analytical tool is helpful to understand business trends

Finding: The above graph and table suggest that around 95% of the organizations are using data analysis tools to understand the business trends in this dynamic business world where everything is changing in a matter of time hence catching up with the new trends will give sustainable advantage to them.

23) Data Analytical tool is helpful to other business functions

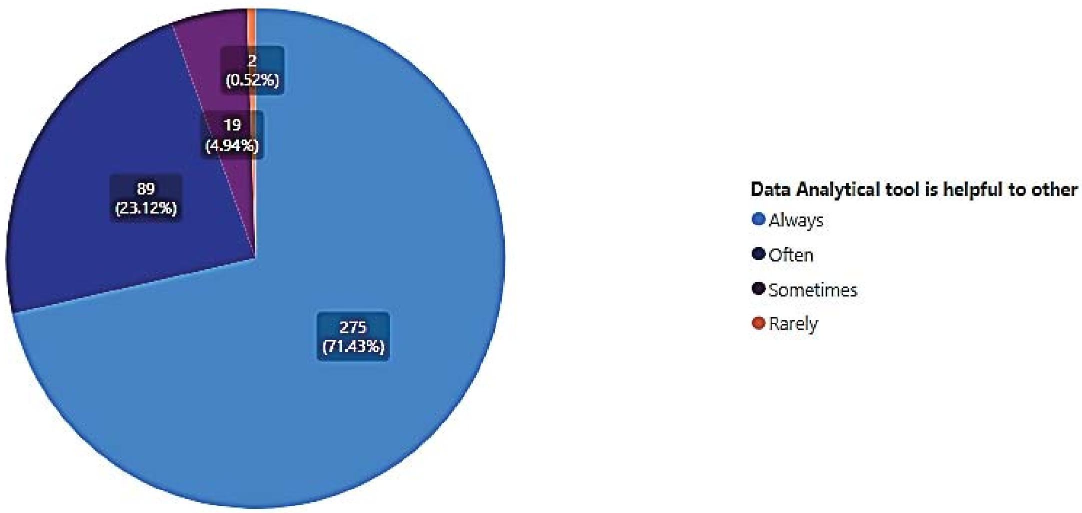

Figure 32: Data Analytical tool is helpful to other business functions

Data Analytical tool is helpful to other	Count
Rarely	2
Sometimes	19
Often	89
Always	275

Table 23: Data Analytical tool is helpful to other

Finding: The above graph and table suggest that around 95% of the organizations are using data analytics tools to help the people from different business functions to get everyone on the same page of business and streamline the operations.

24) Is the performance of your company increased with the usage of data analytical tools?

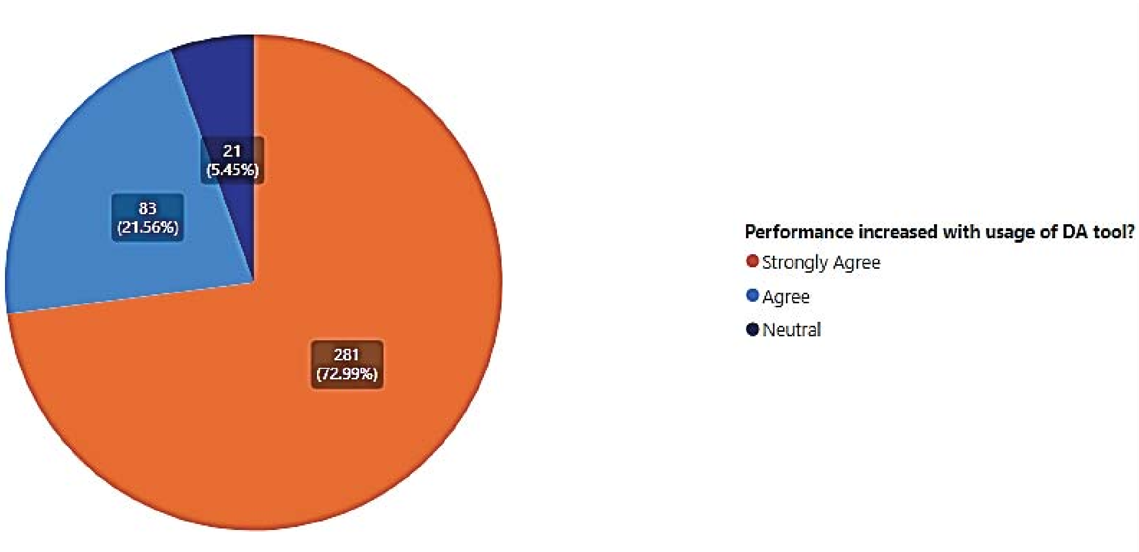

Figure 33: Performance of your company increased with the usage of data analytical tool

Is the performance of your company increased with the usage of data analytical tools?	Count
Neutral	21
Agree	83
Strongly Agree	281

Table 24: Performance of your company increased with the usage of data analytical tool

Finding: The above graph and table suggest that around 95% of the organizations believe that the performance of their respective companies has improved due to the usage of data analytics tools whereas 5% are neutral which means they are not sure whether the performance improvement is because of these data analysis tools or something else.

25) Data analytical tools in your organization based on Strategic decision-making

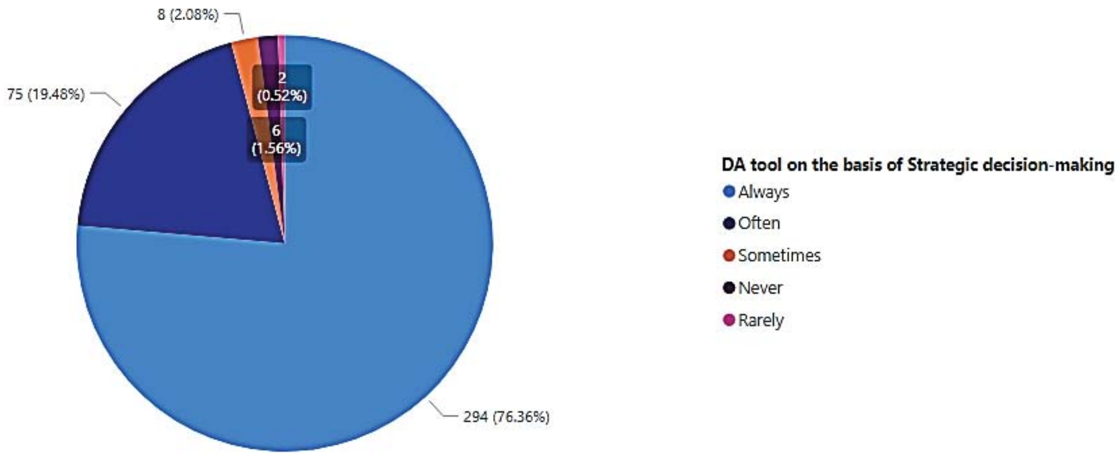

Figure 34: Data analytical tools in your organization based on Strategic decision-making

Data analytical tools in your organization based on Strategic decision-making	Count
Never	6
Rarely	2
Sometimes	8
Often	75
Always	294

Table 25: Data analytical tools in your organization based on Strategic decision-making

Finding: The above graph and table suggest that around 96% of the organizations believe that the selection of the particular data analytics tool is based on strategic decision making the companies are looking out for. So it's a more outcome-oriented approach while selecting the data analytics tool.

26) Data analytical tools in your organization based on Operational decision-making

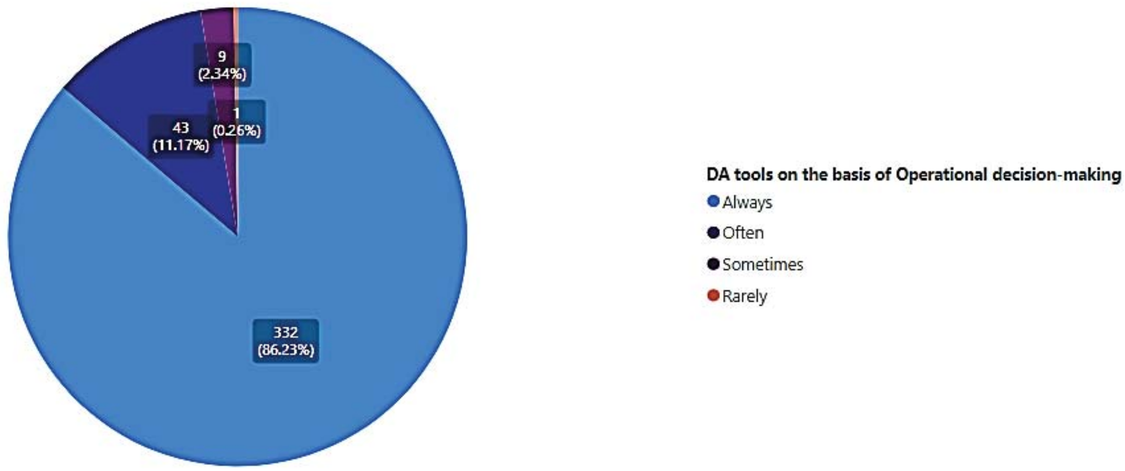

Figure 35:Data analytical tools in your organization based on Operational decision-making

Data analytical tools in your organization based on Operational decision-making	Count
Never	1
Sometimes	9
Often	43
Always	332

Table 26: Data analytical tools in your organization based on Operational decision-making

Finding: The above graph and table suggest that around 97% of the organizations believe that the selection of the particular data analytics tool is based on operational decision making the companies are looking out for. So, it's a more operations-oriented approach while selecting the data analytics tool.

27) Data analytical tools in your organization based on Tactical decision-making

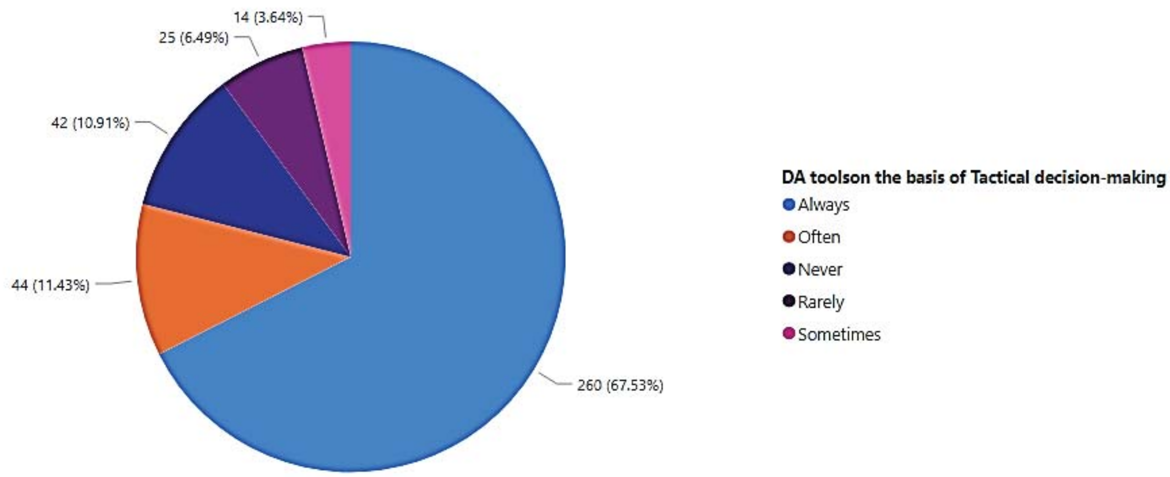

Figure 36: Data analytical tools in your organization based on Tactical decision-making

Data analytical tools in your organization based on Tactical decision-making	Count
Never	42
Rarely	25
Sometimes	14
Often	44
Always	260

Table 27: Data analytical tools in your organization based on Tactical decision-making

Finding: The above graph and table suggest that around 78% of the organizations believe that the selection of the particular data analytics tool is based on tactical decision making the companies are looking out for. So it's a more goal-oriented approach while selecting the data analytics tool.

28) For which purposes do you use data analytics tools?

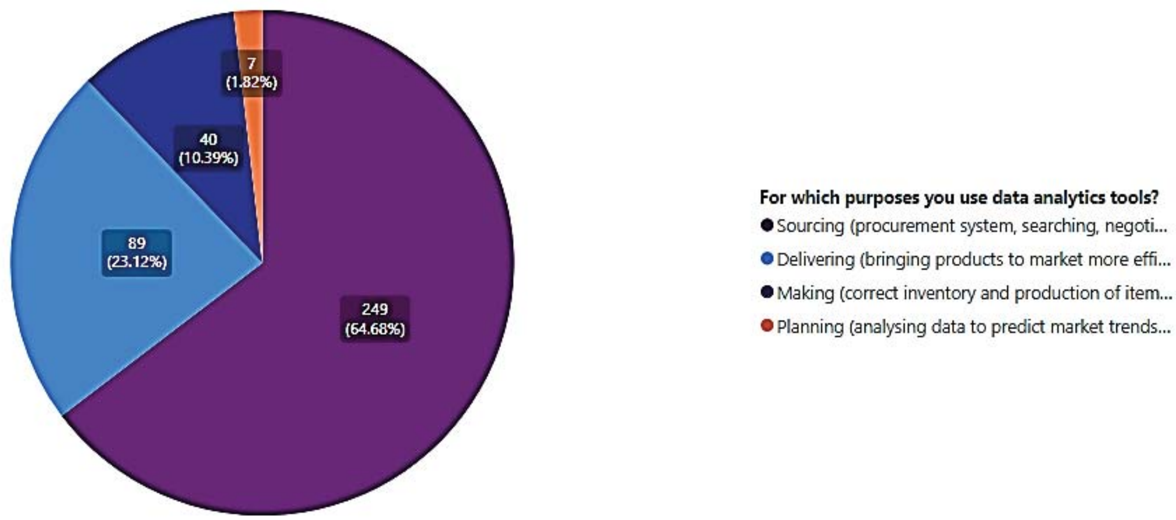

Figure 37: Purposes to use data analytics tools

For which purposes do you use data analytics tools?	Count
Planning (analysing data to predict market trends of products and services)	7
Sourcing (procurement system, searching, negotiating and evaluating suppliers)	249
Making (correct inventory and production of items in terms of time)	40
Delivering (bringing products to market more efficiently)	89

Table 28: Purposes you use data analytics tools

Finding: The above graph and table suggest that around 65% of the organizations believe that sourcing is the key aspect where they use the data analytics tool followed by 23% of organizations that are using data analytics tools to deliver the products and services. Making and planning are the two aspects where they use little or fewer data analytics services.

29) Does your data is following business understanding – data elements as per business engagement points?

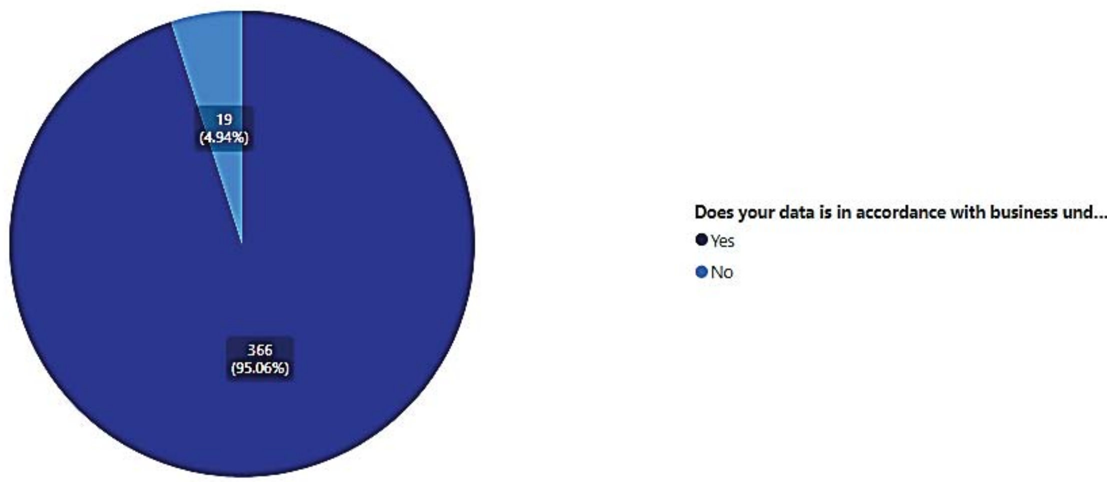

Figure 38: Does your data is following business understanding – data elements as per business engagement points?

Does your data is following business understanding – data elements as per business engagement points?	Count
No	19
Yes	366

Table 29: Does your data is following business understanding – data elements as per business engagement points?

Finding: The above graph and table suggest that around 95% of the organizations believe that they have the understanding of the business they are into and hence they understand the various data elements needed to bring into the picture to create the correct engagement points so that they can understand the business in a more elaborative manner.

30) Do you prepare for data – completeness, consistency, dealing with outliers and redundant variables?

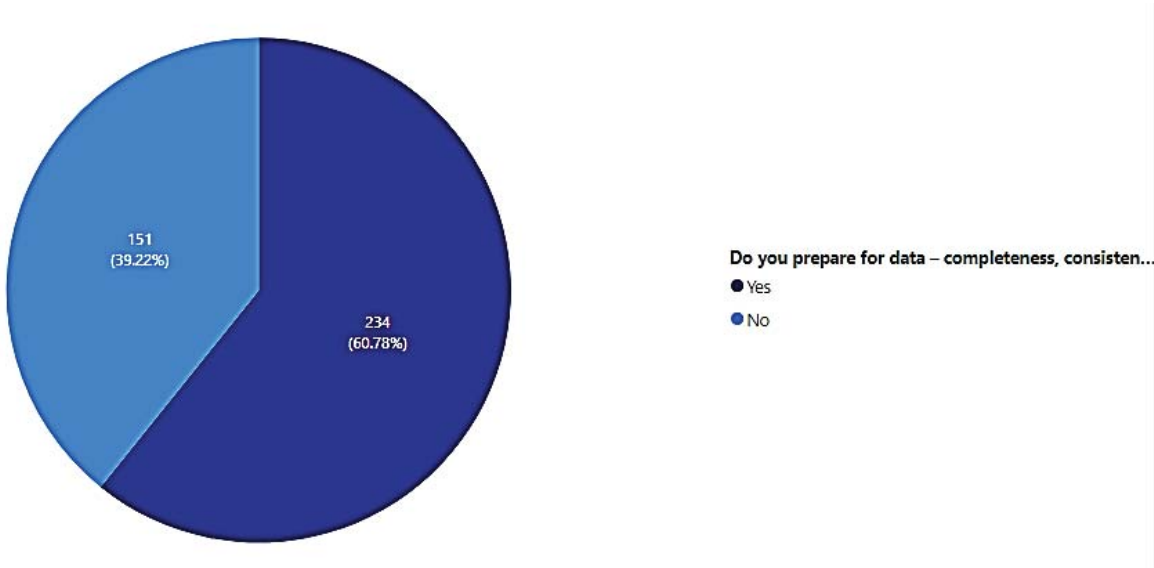

Figure 39: Preparation of Data

Do you prepare for data – completeness, consistency, dealing with outliers and redundant variables?	Count
Yes	234
No	151

Table 30: Preparation of Data

Finding: The above graph and table suggest that around 60% of the organizations believe that their organization is focusing on the way data should be maintained such as to check for completeness, consistency, dealing with the extreme values and redundant variables. 40% of respondents said their organizations do not maintain the data as per the standards.

31) The utility of data analytics tools is used to allow us to select a logical choice from the available options.

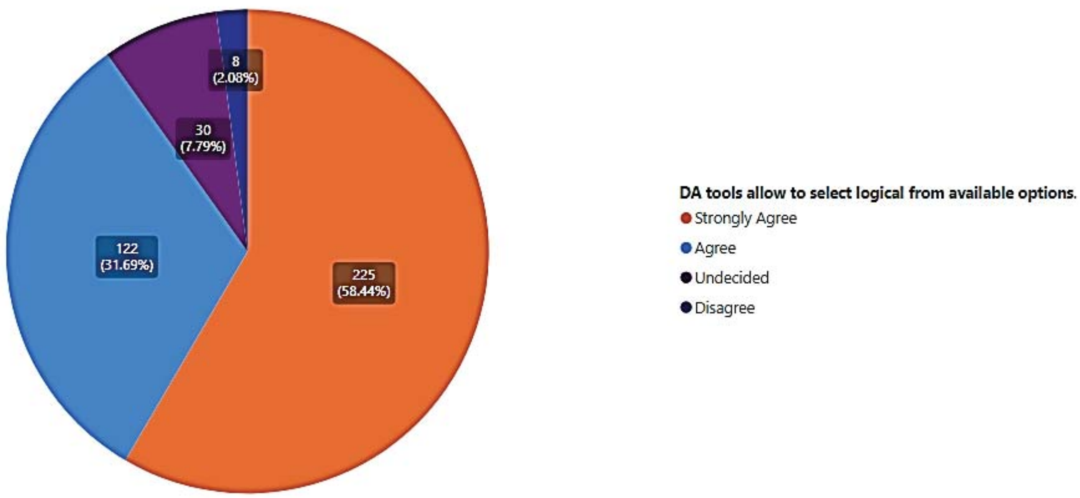

Figure 40: Utility of data analytics tools used to allow to select a logical choice from the available options.

Utility of data analytics tools used to allow us to select a logical choice from the available options	Count
Disagree	8
Undecided	30
Agree	122
Strongly Agree	225

Table 31: Utility of data analytics tools used to allow us to select a logical choice from the available options

Finding: The above graph and table suggest that around 90% of the organizations believe that the selection of the logical choices is allowed by the data analytical tools whereas on the other side 10% of the organizations don't believe in the same manner they believe that it's on and off that the choices selection is available.

32) Utility of data analytics tools used to assist in achieving organizational or managerial objectives or goals.

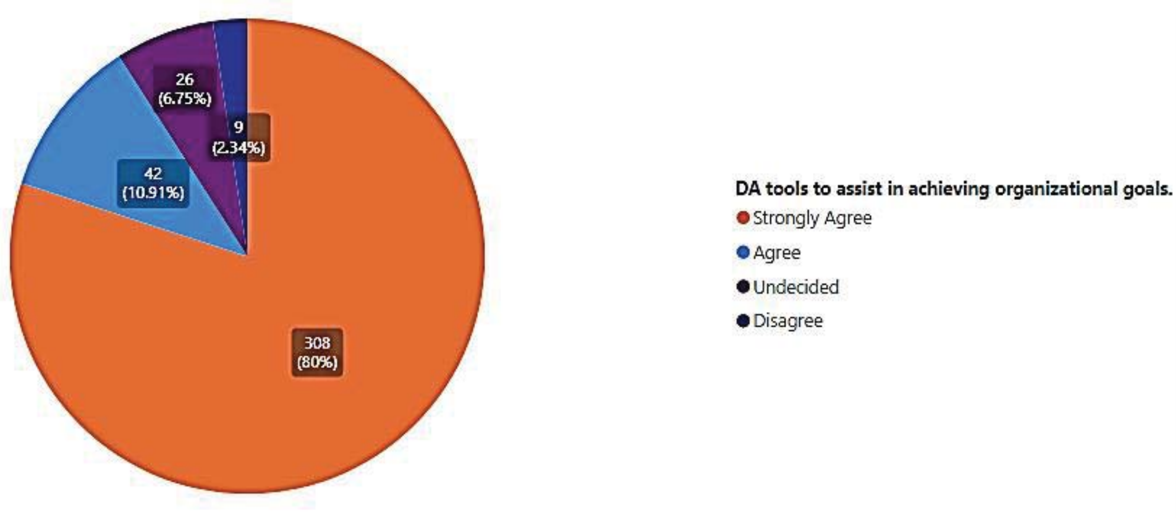

Figure 41:Utility of data analytics tools used to assist in achieving organizational or managerial objectives or goals.

Utility of data analytics tools used to assist us in achieving organizational or managerial objectives or goals.	Count
Disagree	9
Undecided	26
Agree	42
Strongly Agree	308

Table 32: Utility of data analytics tools used to assist us in achieving organizational or managerial objectives or goals.

Finding: The above graph and table suggest that around 91% of the organizations believe that achieving the organizational goals or objectives are very much feasible with a data analytics tool. Whereas 9% of organizations do not believe that the goals or objectives were achieved every time.

33) Utility of data analytics tools used to assist in business activities.

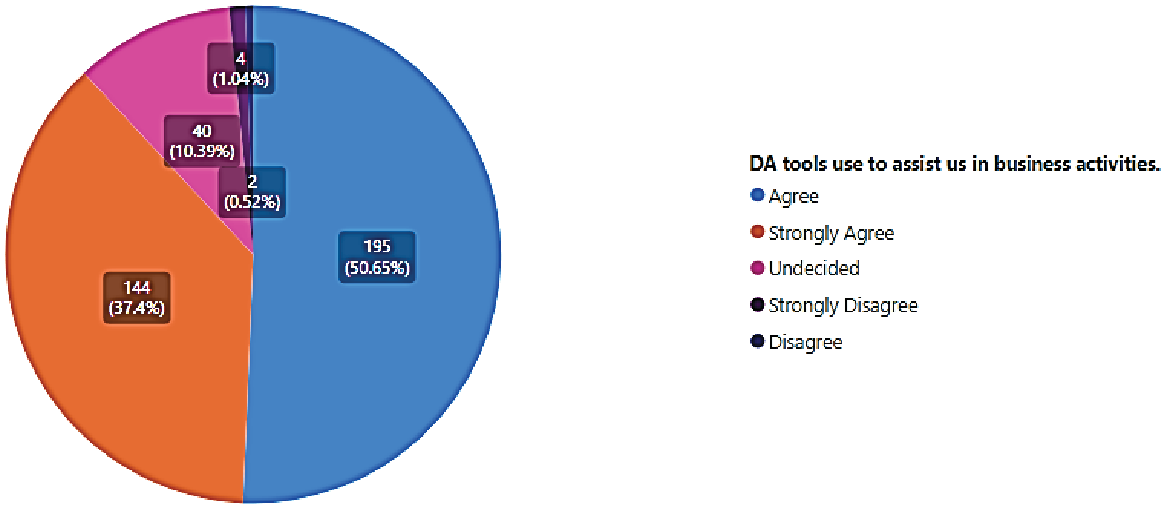

Figure 42: Utility of data analytics tools used to assist in business activities.

Utility of data analytics tools used to assist us in business activities	Count
Strongly Disagree	4
Disagree	2
Undecided	40
Agree	195
Strongly Agree	144

Table 33: Utility of data analytics tools used to assist us in business activities.

Finding: The above graph and table suggest that around 88% of the organizations believe that the data analytics tools help them in performing various business activities in a well-defined manner and can execute those activities in a more precise manner.

34) Data analytics tools use to validate the accuracy and correctness of the information.

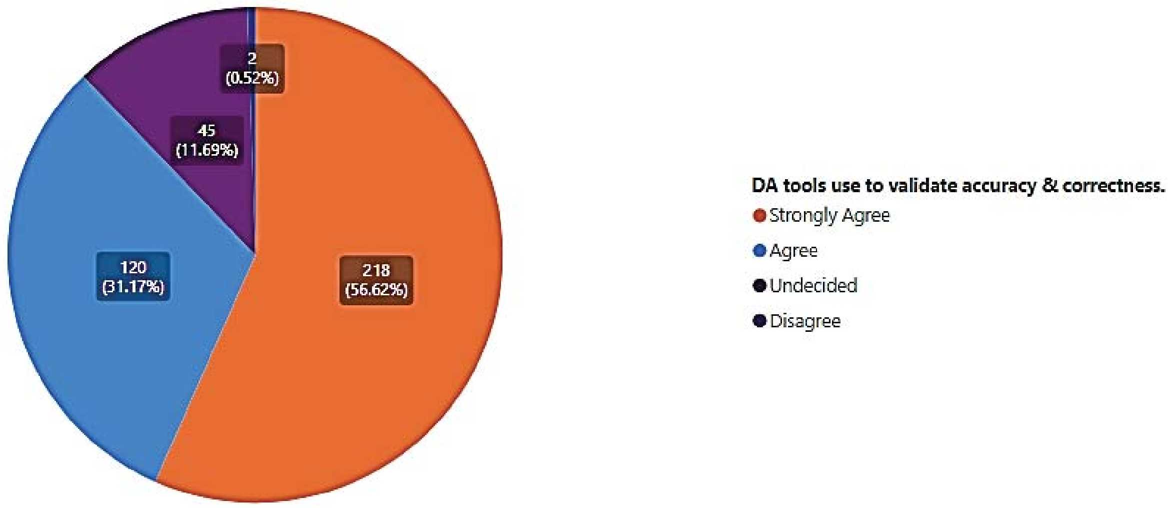

Figure 43: Data analytics tools use to validate the accuracy and correctness of the information.

Tools used to validate the accuracy and correctness of the information	Count
Disagree	2
Undecided	45
Agree	120
Strongly Agree	218

Table 34: Data analytics tools use to validate the accuracy and correctness of the information.

Finding: The above graph and table suggest that around 88% of the organizations believe that the data analytics tools help them to validate the accuracy and correctness of the information whereas 12% of the organizations are still not sure.

35) Utility of data analytics tools that you use to contribute to quality decision making.

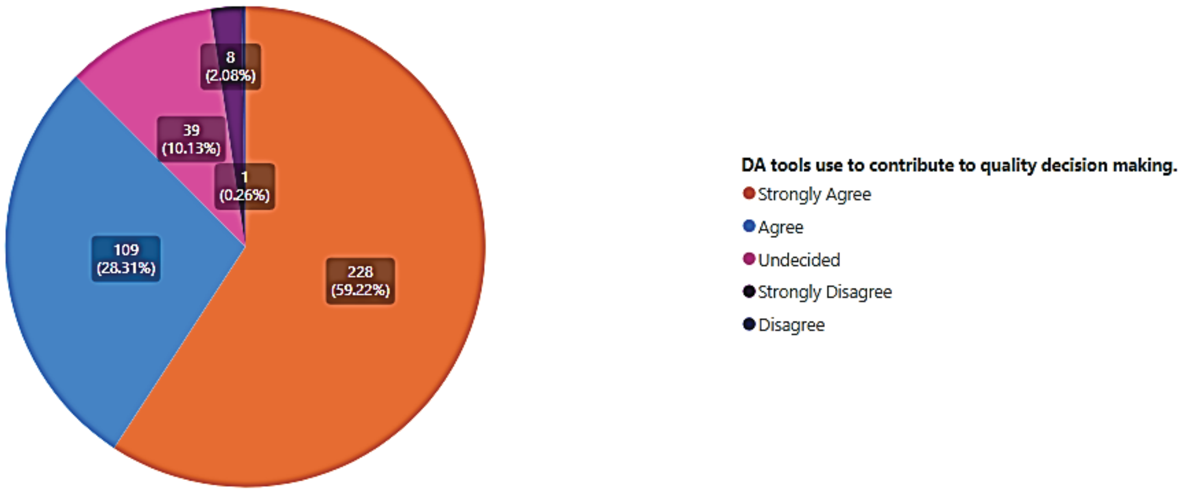

Figure 44: Data analytics tools that you use to contribute to quality decision making

Data analytics tools that you use to contribute to quality decision making	Count
Strongly Disagree	8
Disagree	1
Undecided	39
Agree	109
Strongly Agree	228

Table 35: Data analytics tools that you use to contribute to quality decision making

Finding: The above graph and table suggest that around 89% of the organizations believe that the data analytics tools are used in decision making and the quality of that decision is very good since it is based on the insights generated from the data.

36) Utility of data analytics tools used to transform the processes.

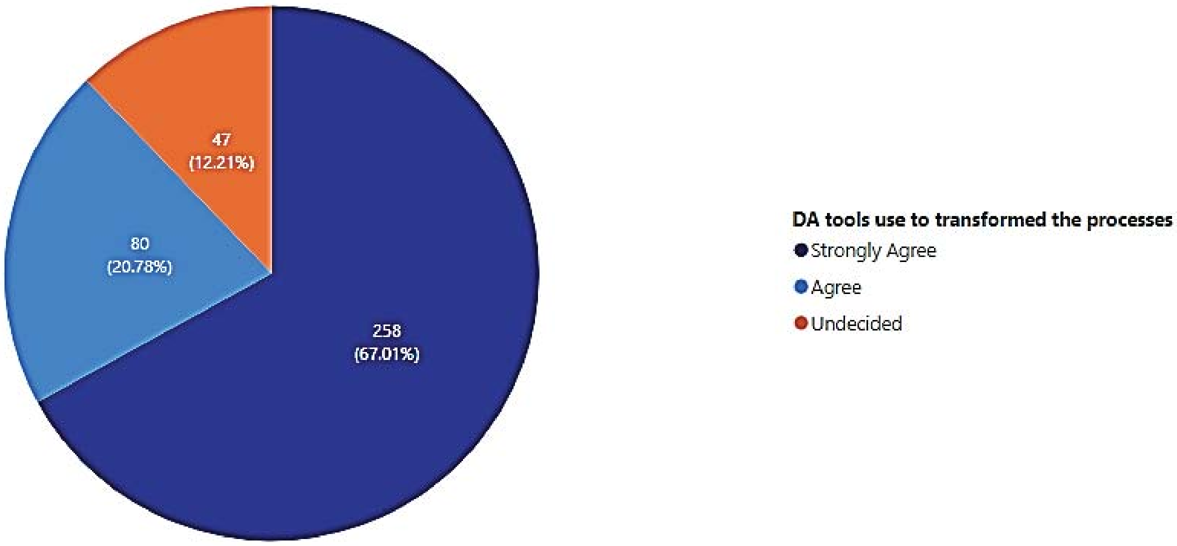

Figure 45: Utility of data analytics tools used to transform the processes.

Utility of data analytics tools used to transform the processes	Count
Undecided	47
Agree	80
Strongly Agree	258

Table 36: Utility of data analytics tools used to transform the processes.

Finding: The above graph and table suggest that around 88% of the organizations believe that the data analytics tools are used in transforming the processes of the organizations since these tools uncover lots trends and patterns and also predicts the outcome and hence the tools are helpful in the transformation of process.

37) Utility of data analytics tools use to integrate the data.

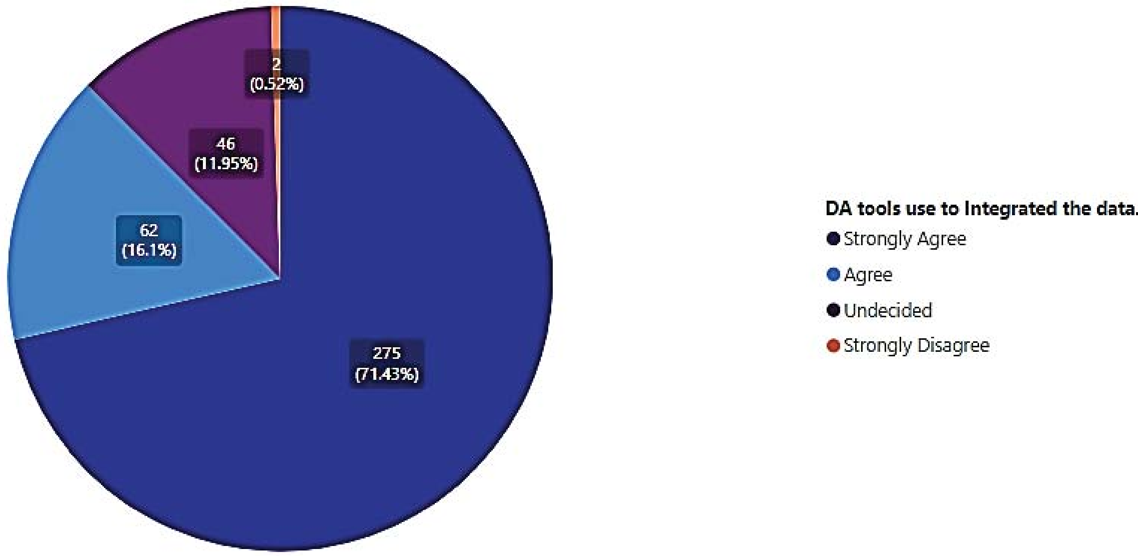

Figure 46: Utility of data analytics tools use to integrate the data.

Utility of data analytics tools use to Integrate the data	Count
Strongly Disagree	2
Undecided	46
Agree	62
Strongly Agree	275

Table 37: Utility of data analytics tools use to integrate the data.

Finding: The above graph and table suggest that around 87% of the organizations believe that the data analytics tools help in understanding the data from a different source such as structured or unstructured and hence it becomes easy for organizations to integrate such data at a broader level of the organization so stakeholders can access it most easily.

38) Utility of data analytics tools use to developed skills.

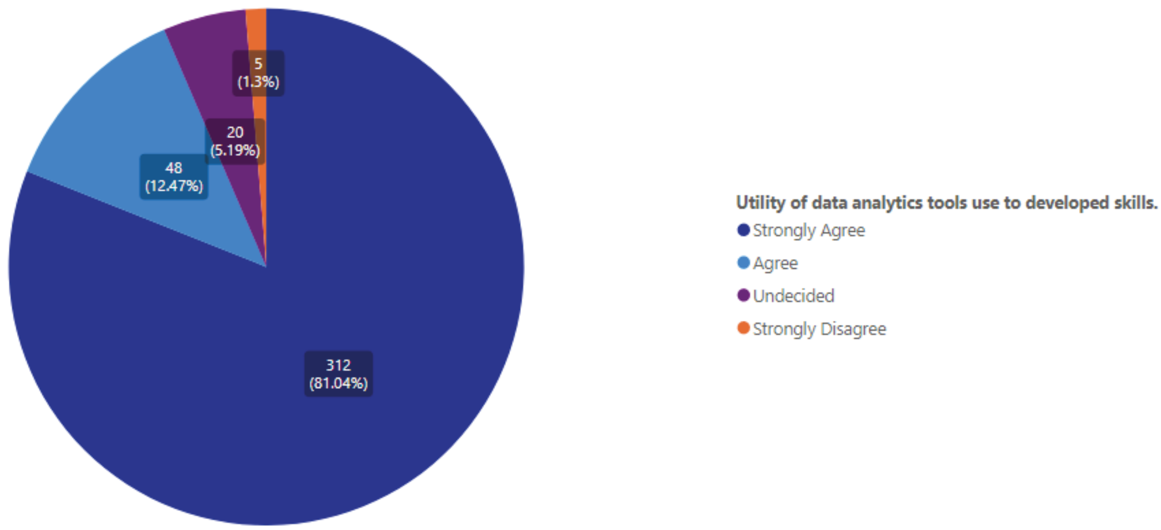

Figure 47: Utility of data analytics tools use to develop skills

Utility of data analytics tools use to developed skills	Count
Strongly Disagree	5
Undecided	20
Agree	48
Strongly Agree	312

Table 38: Utility of data analytics tools use to developed skills

Finding: The above graph and table suggest that around 94% of the organizations believe that the data analytics tools help in understanding the need of the employees who are looking for the skill up-gradation and hence the organizations can design such interventions which can be taken up by an employee to develop their skills.

39) Data analytics tools are used to retain experience and human resources.

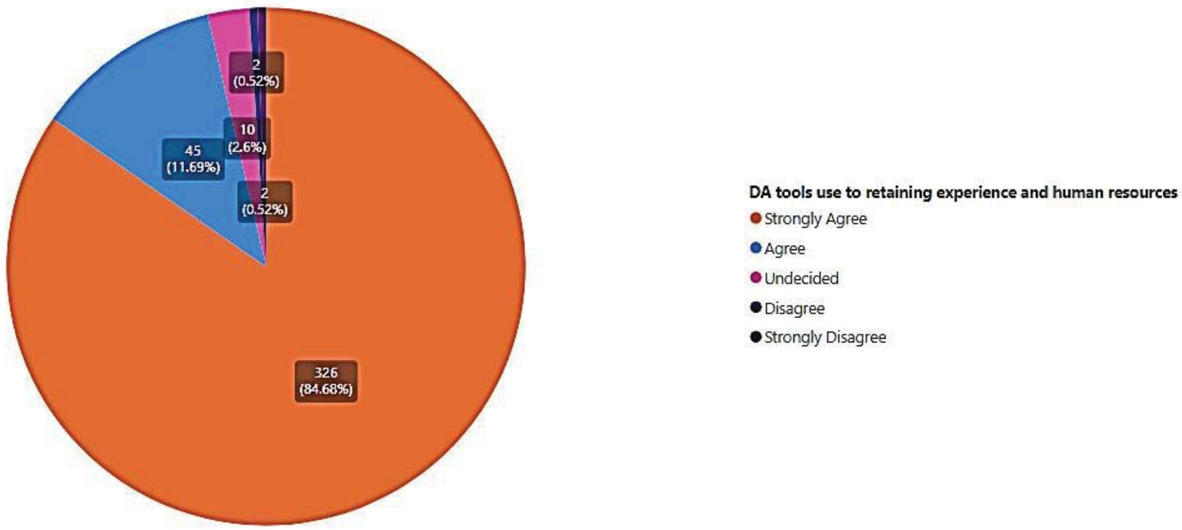

Figure 48: Data analytics tools are used to retain experience and human resources

Data analytics tools are used to retain experience and human resources.	Count
Strongly Disagree	2
Disagree	2
Undecided	10
Agree	45
Strongly Agree	326

Table 39: Data analytics tools are used to retain experience and human resources.

Finding: The above graph and table suggest that around 96% of the organizations believe that the data analytics tools help in understanding the attrition reasons and hence the organizations can design the intervention which ultimately helps in retaining the human resources.

40)	The utility of data analytics tools is used to ensure data quality.

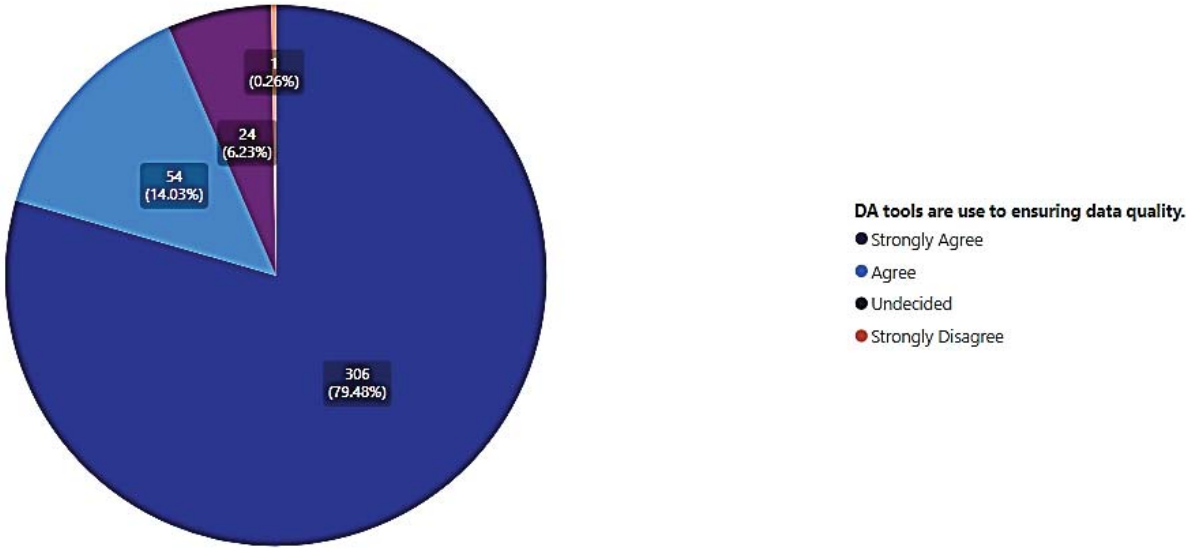

Figure 49: Utility of data analytics tools are used to ensure data quality

Utility of data analytics tools are used to ensure data quality	**Count**
Strongly Disagree	1
Undecided	24
Agree	54
Strongly Agree	306

Table 40: Utility of data analytics tools are used to ensure data quality

Finding: The above graph and table suggest that around 94% of the organizations believe that the data analytics tools help in making sure that the data we are dealing with is of high quality since its outcome will impact the business outcome.

41) The utility of data analytics tools is used to bring flexible systems, collaboration, knowledge exchange, and trust and managing relationships.

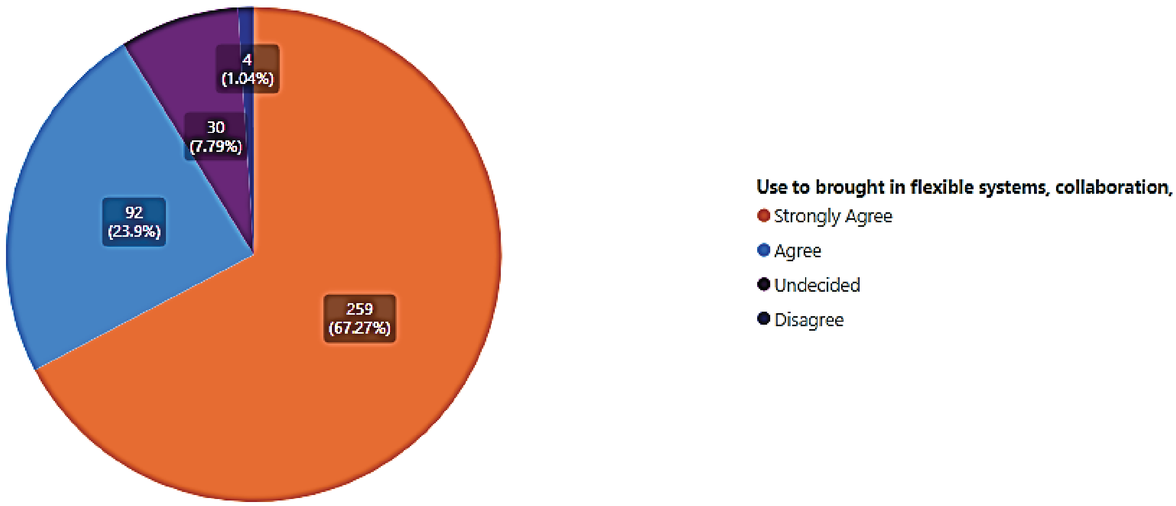

Figure 50: Data analytics tools are used to bring flexible systems, collaboration, knowledge exchange, and trust and managing relationships.

Use to brought flexible systems, collaboration, knowledge exchange, and trust and managed relationships.	**Count**
Disagree	4
Undecided	30
Agree	92
Strongly Agree	259

Table 41: DA tools are used to bring flexible systems, collaboration, knowledge exchange, and trust and managing relationships.

Finding: The above graph and table suggest that around 90% of the organizations believe that the data analytics tools help in expressing the data in such a manner that employees from various business functions can understand it develop their knowledge and collaborate which will build relationships and create agile systems for organizations.

42) Utility of data analytics tools is used to produce near or real-time results by processing and analysing streamed data.

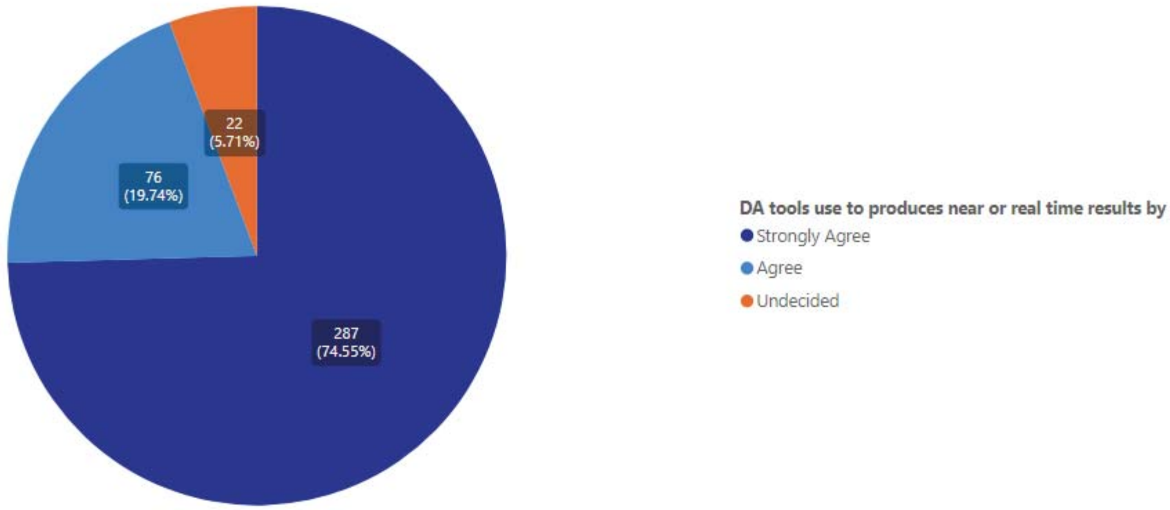

Figure 51: Utility of data analytics tools are used to produce near or real-time results by processing and analysing streamed data.

Tools are used to produce near or real-time results by processing and analysing streamed data	Count
Undecided	22
Agree	76
Strongly Agree	287

Table 42: Utility of data analytics tools are used to produce near or real-time results by processing and analysing streamed data.

Finding: The above graph and table suggest that around 95% of the organizations believe that the data analytics tools help in processing the data in real time. The sophisticated machine learning or data science algorithm analyse the real time data.

43) The utility of data analytics tools is used to help business managers to make informed decisions.

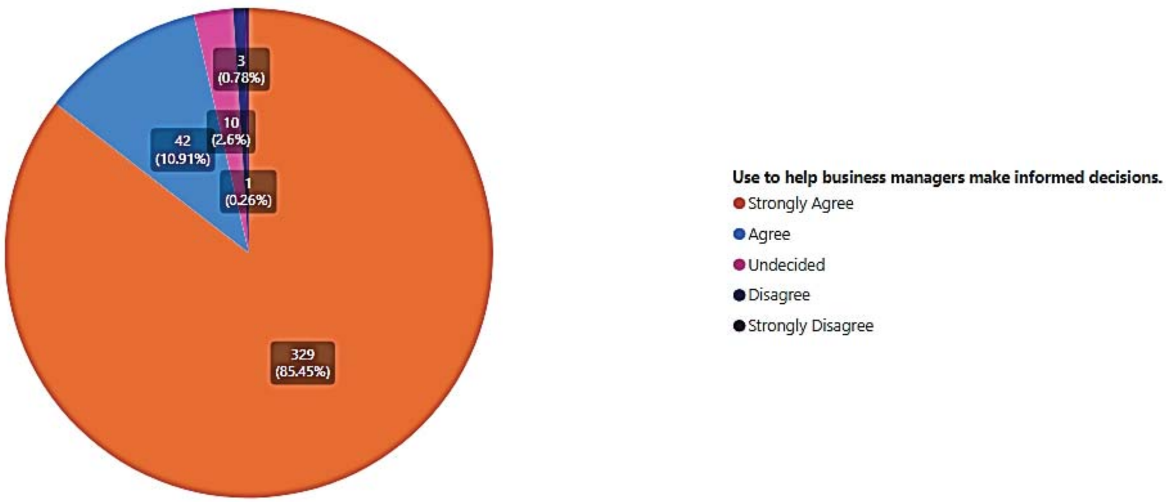

Figure 52: Utility of data analytics tools is used to help business managers to make informed decisions.

The utility of data analytics tools is used to help business managers make informed decisions.	**Count**
Strongly Disagree	1
Disagree	3
Undecided	10
Agree	42
Strongly Agree	329

Table 43: Utility of data analytics tools are used to help the business managers make informed decisions.

Finding: The above graph and table suggest that around 96% of the organizations believe that the data analytics tools help managers to make better decision based on the insights generated out of these tools.

44) The utility of data analytics tools are used to help the business managers to drive the company forward.

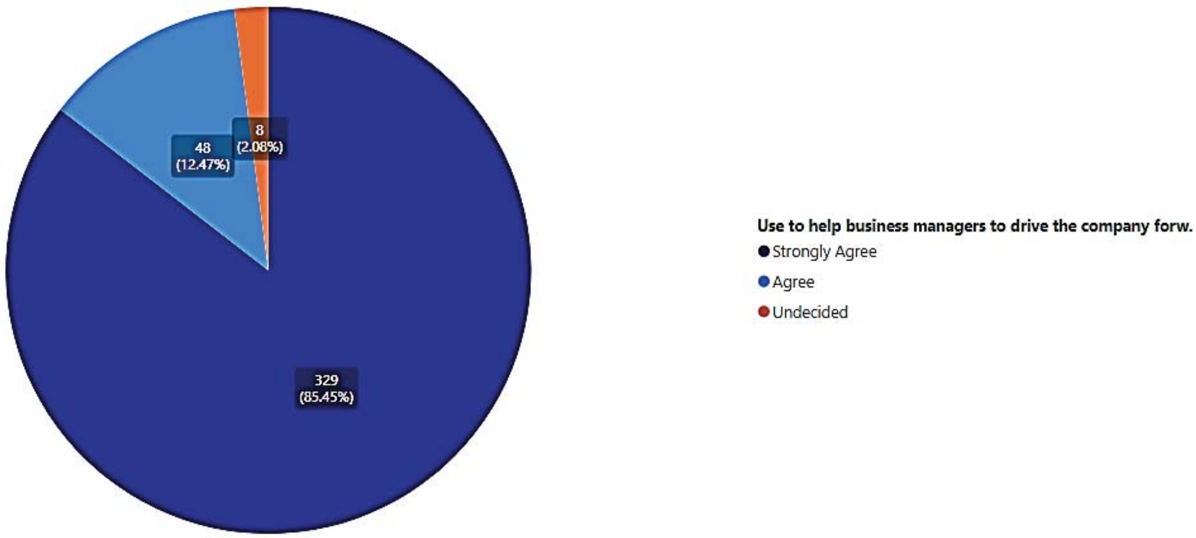

Figure 53: Utility of data analytics tools are used to help the business managers to drive the company forward.

Utility of data analytics tools are used to help the business managers to drive the company forward	Count
Undecided	8
Agree	48
Strongly Agree	329

Table 44: Utility of data analytics tools are used to help the business managers to drive the company forward.

Finding: The above graph and table suggest that around 98% of the organizations believe that the data analytics tools help their managers to chalk out a path towards more progress as these tools help in uncovering the areas which can be of great value to the organizations.

45) Utility of data analytics tools are used to help business managers to improve efficiency.

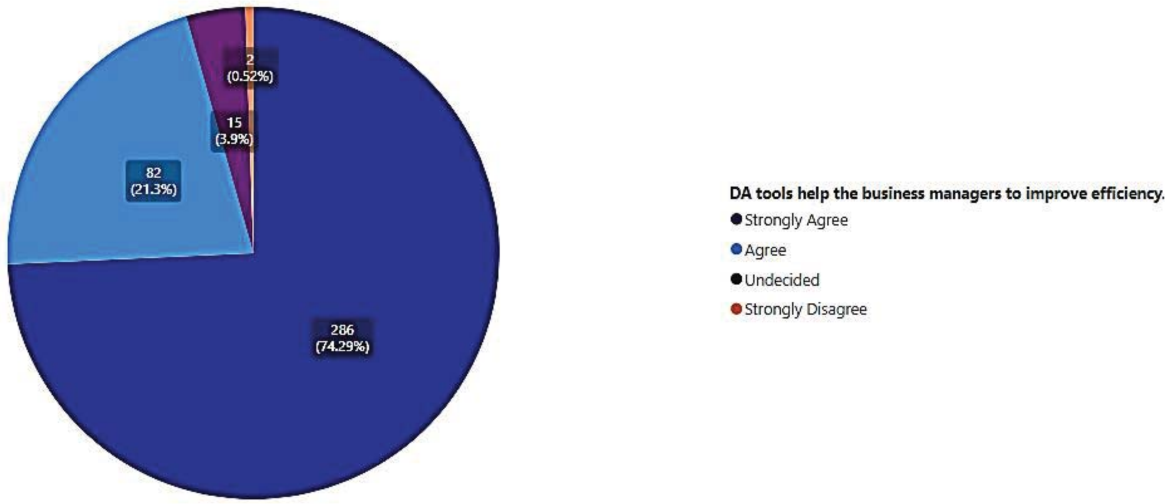

Figure 54: Utility of data analytics tools are used to help the business managers to improve efficiency.

The utility of data analytics tools is used to help business managers to improve efficiency.	Count
Strongly Disagree	2
Undecided	15
Agree	82
Strongly Agree	286

Table 45: Utility of data analytics tools are used to help the business managers to improve efficiency.

Finding: The above graph and table suggest that around 96% of the organizations believe that the data analytics tools help their business managers to improve the efficiency of the employees by focusing precisely on the areas which need improvement.

46) The utility of data analytics tools are used to replace intuition and guesswork in their decision-making.

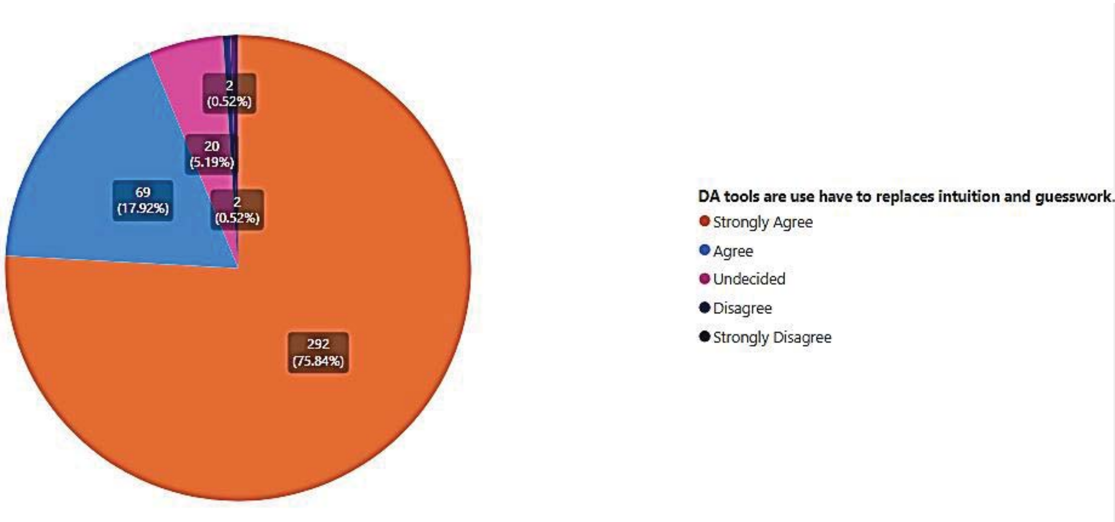

Figure 55: Utility of data analytics tools are used to replace intuition and guesswork in their decision-making.

Utility of data analytics tools are used have to replace intuition and guesswork in their decision-making	Count
Strongly Disagree	2
Disagree	2
Undecided	20
Agree	69
Strongly Agree	292

Table 46: Utility of data analytics tools are used to replace intuition and guesswork in their decision-making.

Finding: The above graph and table suggest that around 94% of the organizations believe that the data analytics tools help in more confident decision making by replacing the guesswork due to the presence of insights generated through the analytics tools.

47) The utility of data analytics tools are used to help in defining the problem to be addressed.

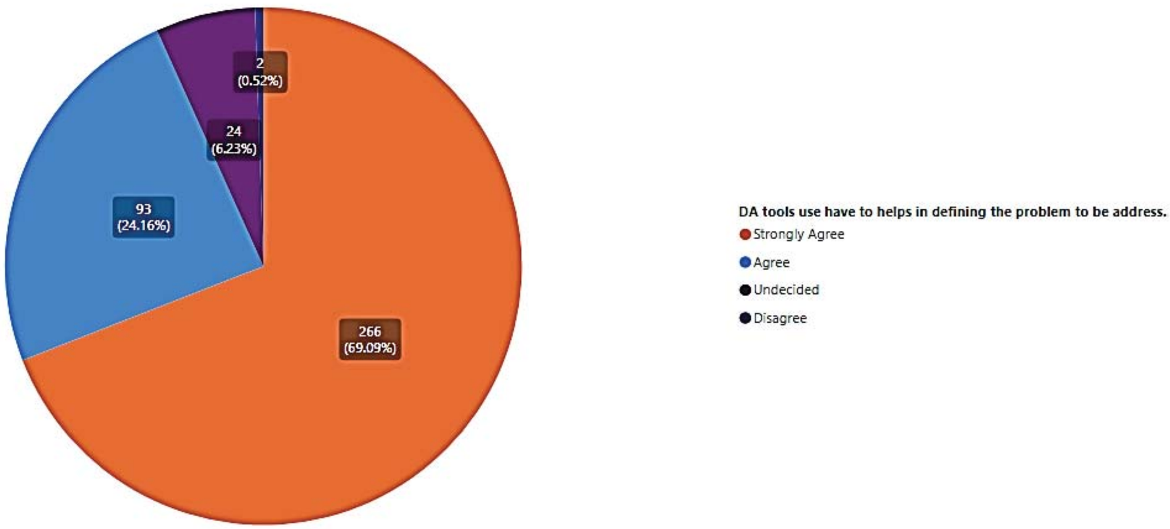

Figure 56: Utility of data analytics tools are used to help in defining the problem to be addressed.

The utility of data analytics tools is used to help in defining the problem to be addressed	Count
Disagree	2
Undecided	24
Agree	93
Strongly Agree	266

Table 47: Utility of data analytics tools is used to help in defining the problem to be addressed.

Finding: The above graph and table suggest that around 94% of the organizations believe that the data analytics tools help in exploring the data to understand the problem at its core area and helps in defining the problem in a good manner.

48) The utility of data analytics tools is used to make decision-making more transparent, accurate, efficient, and to some extent faster.

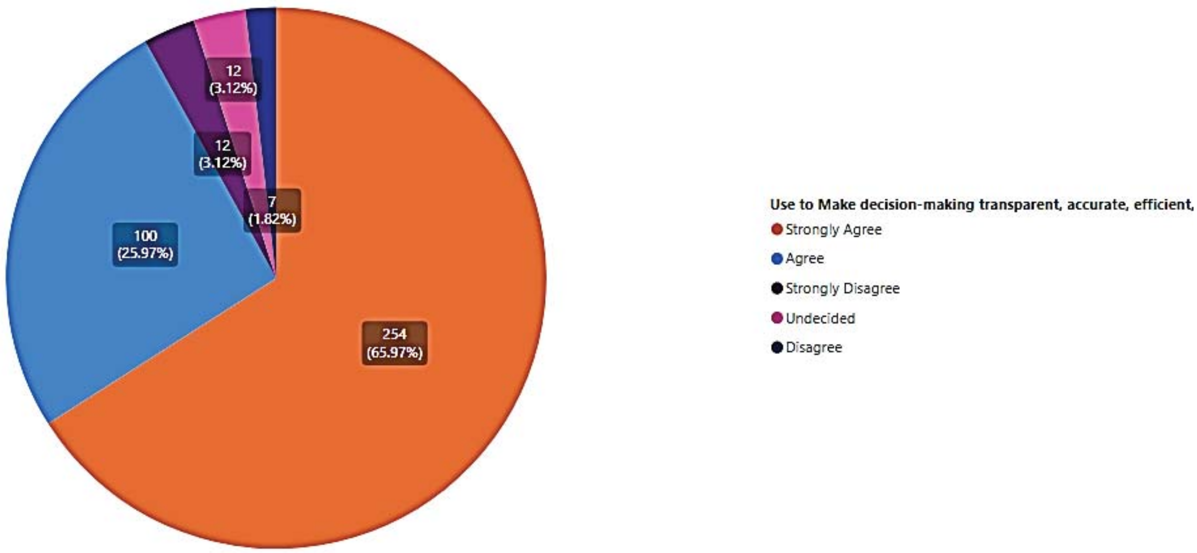

Figure 57: Utility of data analytics tools are used to make decision-making more transparent, accurate, efficient, and to some extent faster.

The utility of data analytics tools is used to make decision-making more transparent, accurate, efficient, and to some extent faster	Count
Strongly Disagree	12
Disagree	7
Undecided	12
Agree	100
Strongly Agree	254

Table 48: Utility of data analytics tools are used to make decision-making more transparent, accurate, efficient, and to some extent faster.

Finding: The above graph and table suggest that around 91% of the organizations believe that the data analytics tools help in taking decisions at a faster rate and also with more accuracy and transparency.

49) The utility of data analytics tools is used to influence the traditional roles of individuals.

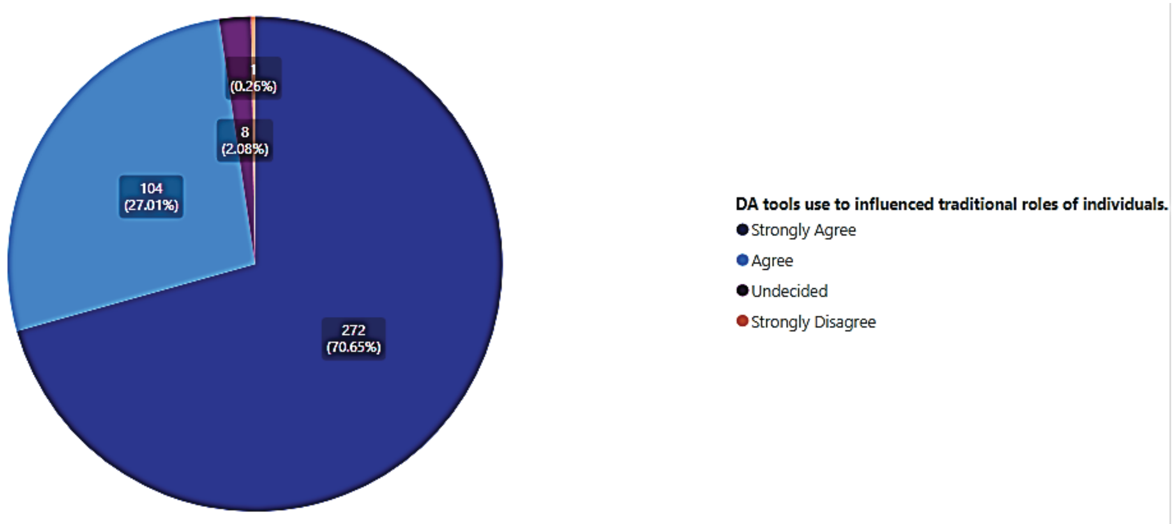

Figure 58: Utility of data analytics tools are used to influence the traditional roles of the individuals.

The utility of data analytics tools is used to influence the traditional roles of individuals.	Count
Strongly Disagree	1
Undecided	8
Agree	104
Strongly Agree	272

Table 4.49: Utility of data analytics tools are used to influence the traditional roles of the individuals.

Finding: The above graph and table suggest that around 98% of the organizations believe that the data analytics tools have influenced the employees because the data analytics tools have changed how one has to look at the data and decisions made based on that, hence now the employee want to upgrade them in a data-driven culture.

50) Data Analytics has become an integral part of organizational business processes.

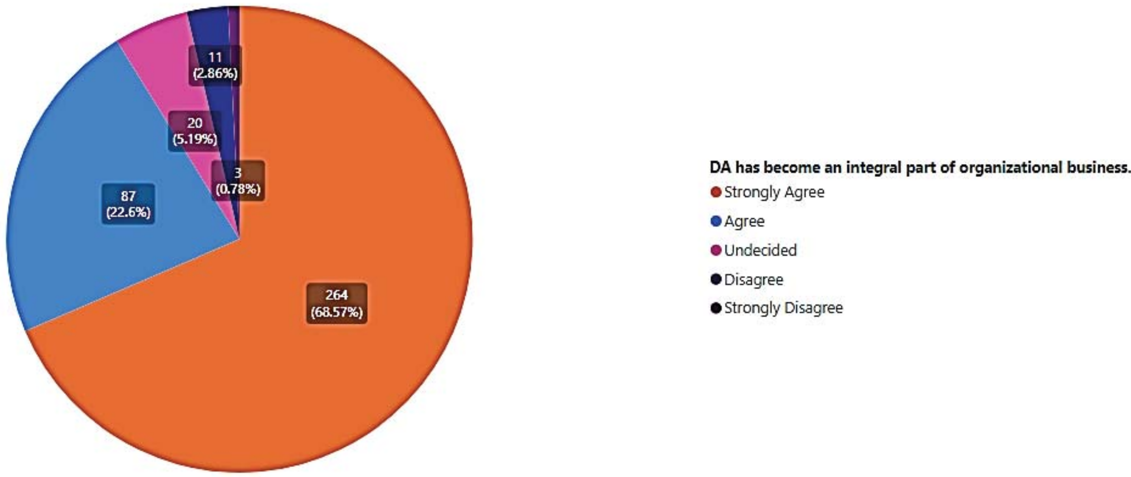

Figure 59: Data Analytics has become an integral part of organizational business processes.

Data Analytics has become an integral part of organizational business processes.	**Count**
Strongly Disagree	3
Disagree	11
Undecided	20
Agree	87
Strongly Agree	264

Table 50: Data Analytics has become an integral part of organizational business processes.

Finding: The above graph and table suggest that around 91% of the organizations believe that data analytics are nowadays an integral part of the business process, this shows how important it is for the business.

51) Data Analytics has changed the way organizations are built and function.

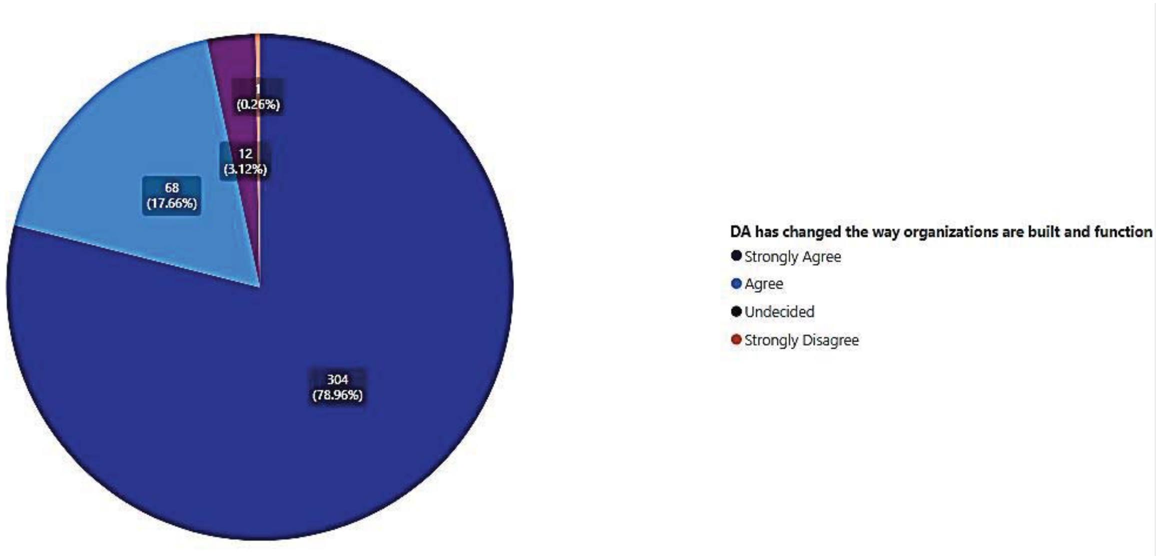

Figure 60: Data Analytics has changed the way organizations are built and function

Data Analytics has changed the way organizations are built and function	**Count**
Strongly Disagree	1
Undecided	12
Agree	68
Strongly Agree	304

Table 51: Data Analytics has changed the way organizations are built and function

Finding: The above graph and table suggest that around 97% of the organizations believe that data analytics has changed how organizations should structure themselves to remain relevant in today's times.

52) Data Analytics lead to undergoing thorough business process changes, applying change management practices for business processes.

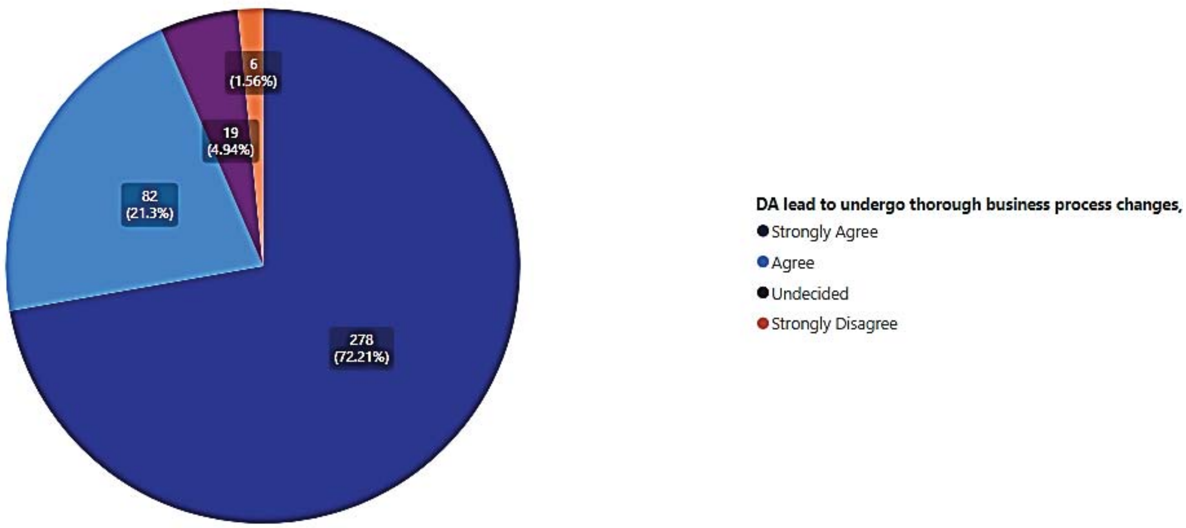

Figure 61:Data Analytics lead to undergoing thorough business process changes, applying change management practices for business processes.

Data Analytics lead to undergoing thorough business process changes, applying change management practices for business processes.	Count
Strongly Disagree	6
Undecided	19
Agree	82
Strongly Agree	278

Table 52: Data Analytics lead to undergoing thorough business process changes, applying change management practices for business processes.

Finding: The above graph and table suggest that around 93% of the organizations believe that data analytics adoption by the organizations has made them undertake change management practice to fully engross the data-driven culture.

53) Data Analytics brings cost advantages to the business.

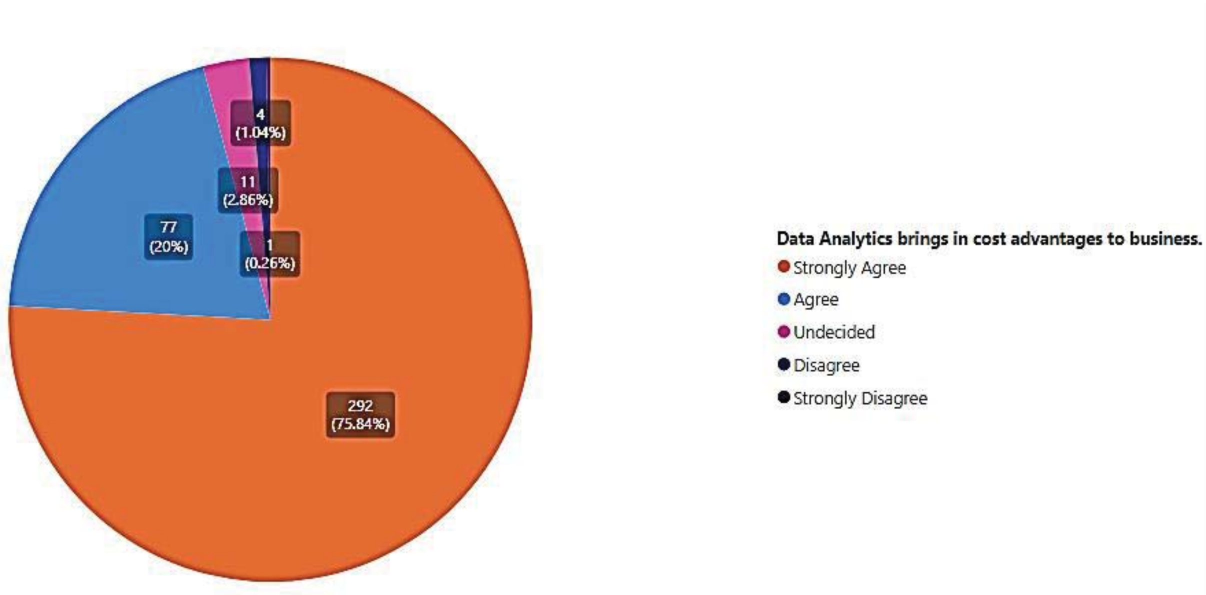

Figure 62:Data Analytics brings cost advantages to the business.

Data Analytics brings in cost advantages to the business	Count
Strongly Disagree	1
Disagree	4
Undecided	11
Agree	77
Strongly Agree	292

Table 53: Data Analytics brings cost advantages to the business.

Finding: The above graph and table suggest that around 96% of the organizations believe that data analytics gives cost advantages to the organizations because these tools help them to understand the pitfall areas and also the areas of success and improvement and hence it can save cost as well as generate more revenue to the organizations.

54) Data Analytics help businesses analyse data immediately and make quick decisions based on the learnings.

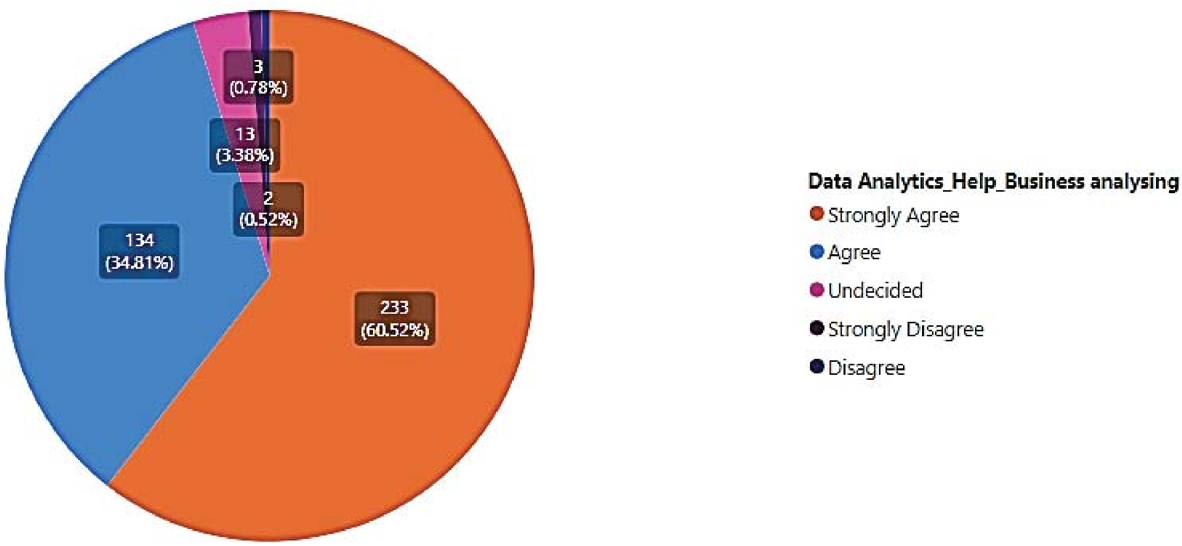

Figure 63: Data Analytics help businesses analyse data immediately and make quick decisions based on the learnings

Data Analytics help businesses analyse data immediately and make quick decisions based on the learnings	**Count**
Strongly Disagree	3
Disagree	2
Undecided	13
Agree	134
Strongly Agree	233

Table 54: Data Analytics help businesses to analyse data immediately and make quick decisions based on the learnings

Finding: The above graph and table suggest that around 95% of the organizations believe that data analytics has helped the organizations in terms of learnings based on data analytics-oriented decisions since these can be made quickly with accuracy.

55) Data Analytics help organizations to create new growth opportunities and entirely new categories of companies that can combine and analyse industry data.

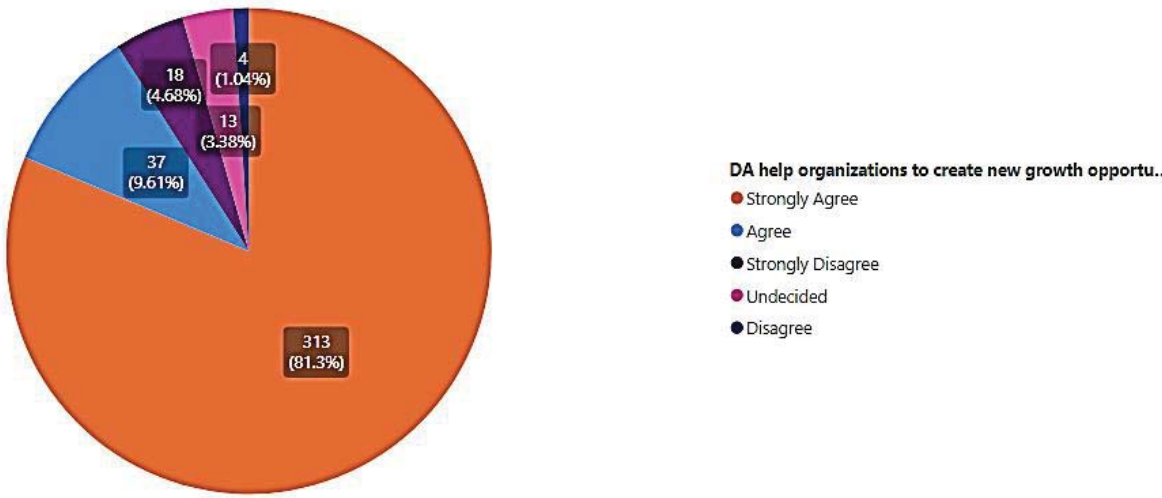

Figure 64: Data Analytics help organizations to create new growth opportunities and entirely new categories of companies that can combine and analyse industry data.

Data Analytics help organizations to create new growth opportunities and entirely new categories of companies that can combine and analyse industry data.	**Count**
Strongly Disagree	18
Disagree	4
Undecided	13
Agree	37
Strongly Agree	313

Table 55: Data Analytics help organizations to create new growth opportunities and entirely new categories of companies that can combine and analyse industry data.

Finding: The above graph and table suggest that around 91% of the organizations believe that data analytics has shown the pathway to them to capture the new opportunities of the businesses and also even to start new organizations by analysing the industry data at large.

56) Data Analytics understands and optimizes business processes.

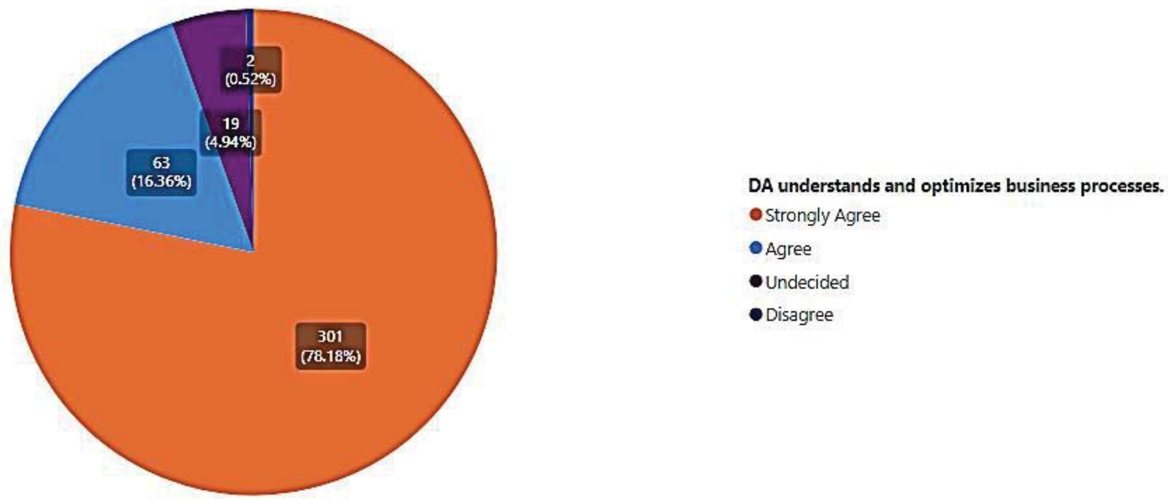

Figure 65: Data Analytics understands and optimizes business processes.

Data Analytics understands and optimizes business processes.	Count
Disagree	2
Undecided	19
Agree	63
Strongly Agree	301

Table 56: Data Analytics understands and optimizes business processes.

Finding: The above graph and table suggest that around 96% of the organizations believe that data analytics has helped them in optimizing their business process which is important to sustain and grow in the long term. The business processes are always at the heart of the organization because it keeps different business verticals together.

57) Inhibitors in Data Analytics Adoption/Implementation without good data quality, the trust in data analytics projects suffers.

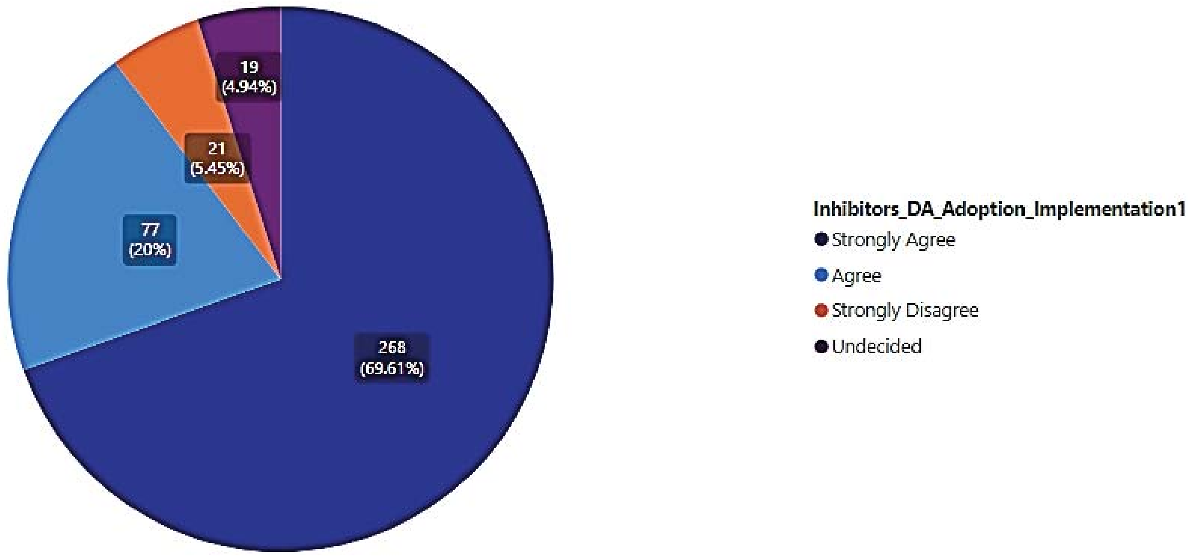

Figure 66: Inhibitors in Data Analytics Adoption/Implementation without good data quality, the trust in data analytics projects suffers.

Inhibitors in Data Analytics Adoption/Implementation without good data quality, the trust in data analytics projects suffers.	**Count**
Strongly Disagree	21
Undecided	19
Agree	77
Strongly Agree	268

Table 57: Inhibitors in Data Analytics Adoption/Implementation without good data quality, the trust in data analytics projects suffers.

Finding: The above graph and table suggest that around 90% of the organizations believe that bad data put the adoption or implementation of analytics at risk because of which business can suffer losses.

58) Inhibitors in Data Analytics Adoption/Implementation data quality is low, and the users do not trust the data, decision-making could be taken out of false promises.

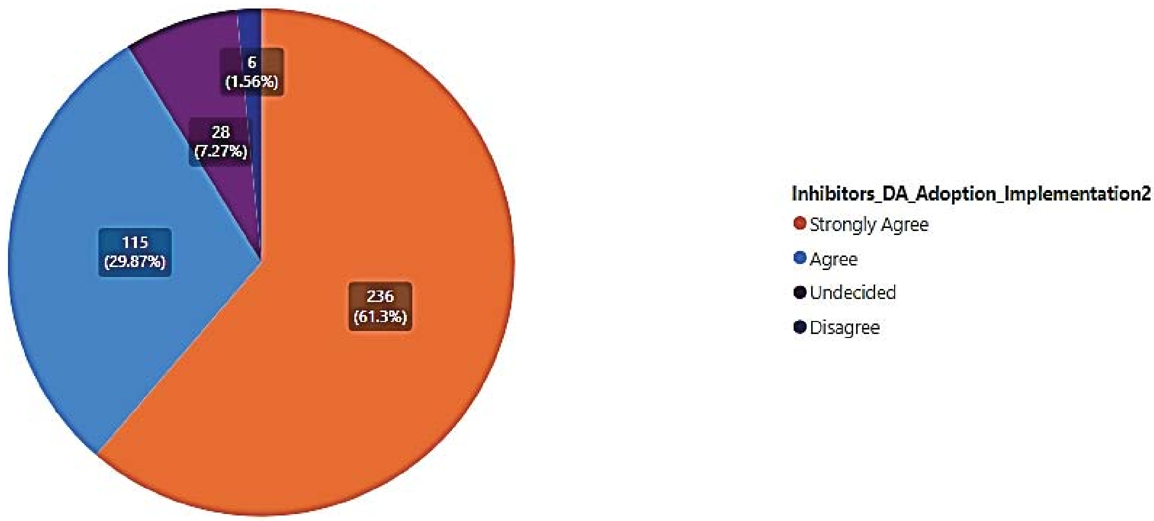

Figure 67: Inhibitors in Data Analytics Adoption/Implementation data quality is low, and the users do not trust the data, decision-making could be taken out of false promises.

Inhibitors in Data Analytics Adoption/Implementation data quality is low, and the users do not trust the data, decision-making could be taken out of false promises.	**Count**
Disagree	6
Undecided	28
Agree	115
Strongly Agree	236

Table 58: Inhibitors in Data Analytics Adoption/Implementation data quality is low, and the users do not trust the data, decision-making could be taken out of false promises.

Finding: The above graph and table suggest that around 91% of the organizations believe that if the trust of the stakeholders in the data is low the decision taken based on such data will put the organizations at risk, hence the trust in data is also and inhibition for the organization to adopt or implement analytics at large.

59) Inhibitors in Data Analytics Adoption/Implementation MSMEs lacks financial strength, has tight budgets.

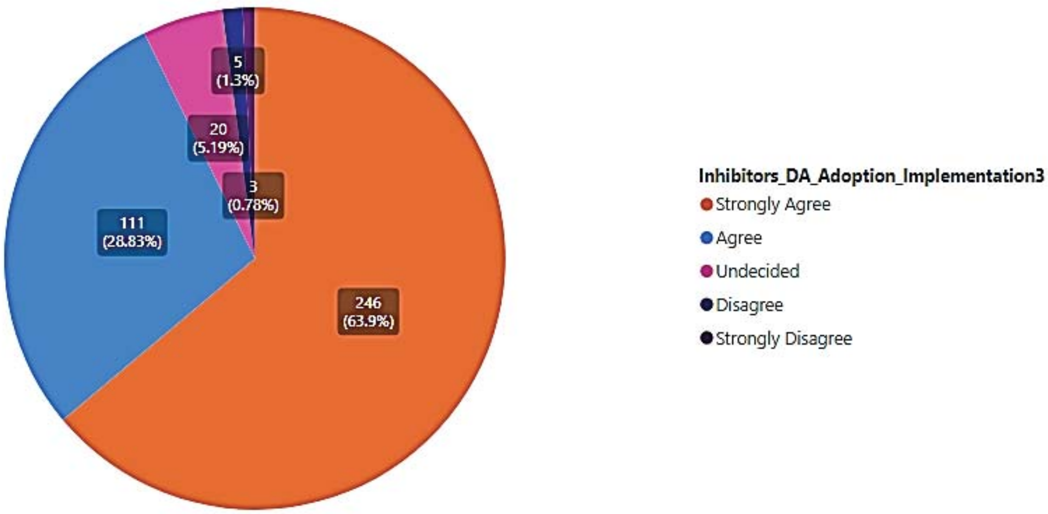

Figure 68: Inhibitors in Data Analytics Adoption/Implementation MSMEs lacks financial strength, has tight budgets.

Inhibitors in Data Analytics Adoption/Implementation MSMEs lacks financial strength, has tight budgets.	**Count**
Strongly Disagree	3
Disagree	5
Undecided	20
Agree	111
Strongly Agree	246

Table 59: Inhibitors in Data Analytics Adoption/Implementation MSMEs lacks financial strength, has tight budgets.

Finding: The above graph and table suggest that around 93% of the organizations believe that MSMEs have financial crunches and also runs on very tight budgets, as there are open source and licensed software for data analytics that's why most of the MSMEs prefer to have the open-source software because of this budget constraints and lesser number of companies adapt to the license version.

60) Inhibitors in Data Analytics Adoption/Implementation there is a lack of sponsors to have the money for Data analytics project implementation.

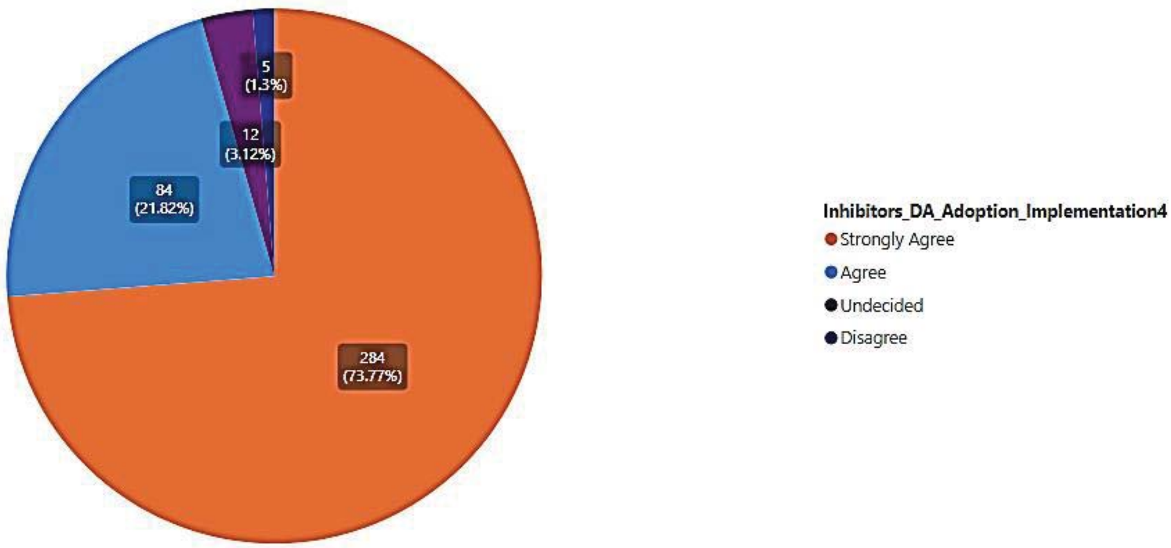

Figure 69: Inhibitors in Data Analytics Adoption/Implementation there isa lack of sponsors to have the money for Data analytics project implementation.

Inhibitors in Data Analytics Adoption/Implementation there isa lack of sponsors to have the money for Data analytics project implementation.	Count
Disagree	5
Undecided	12
Agree	84
Strongly Agree	284

Table 60: Inhibitors in Data Analytics Adoption/Implementation there is a lack of sponsors to have the money for Data analytics project implementation.

Finding: The above graph and table suggest that around 95% of the organizations believe that data analytics adoption or implementation can be hindered due to the lack of sponsorship from top management for the budgets.

61) Inhibitors in Data Analytics Adoption/Implementation there is a lack of experience and understanding possibilities amongst MSME.

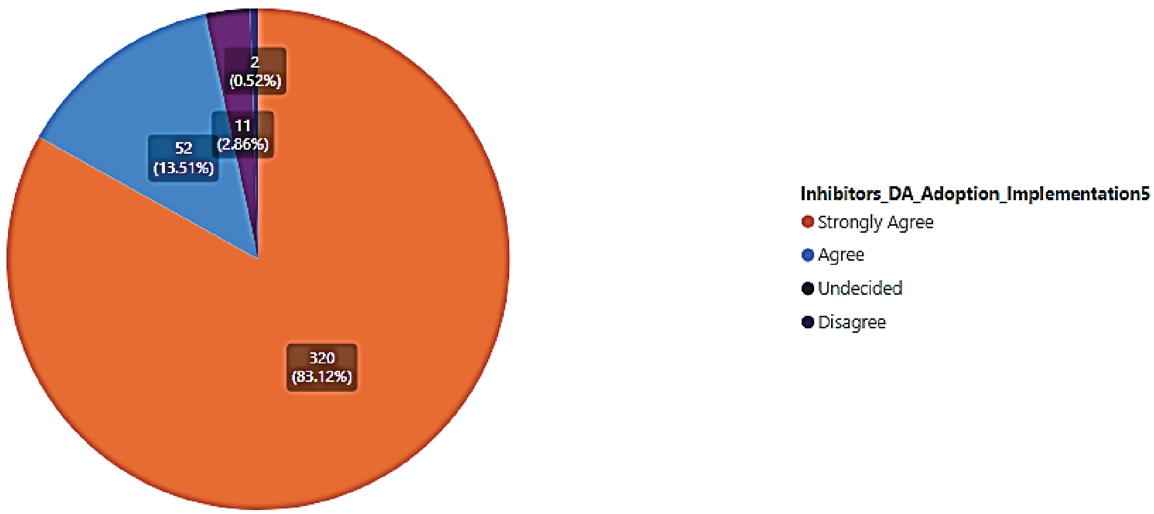

Figure 70: Inhibitors in Data Analytics Adoption/Implementation there is a lack of experience and understanding possibilities amongst MSME.

Inhibitors in Data Analytics Adoption/Implementation there is a lack of experience and understanding possibilities amongst MSME.	Count
Disagree	2
Undecided	11
Agree	52
Strongly Agree	320

Table 61: Inhibitors in Data Analytics Adoption/Implementation there is a lack of experience and understanding possibilities amongst MSME.

Finding: The above graph and table suggest that around 97% of the organizations believe that the knowledge and experience required to understand the possibilities of introducing the data analytics can also serve as the hindrance in the adoption and implementation of the data analytics practice within these MSME's.

62) Inhibitors in Data Analytics Adoption/Implementation not being aware of data analytics possibilities and fail to see the value of data analytics.

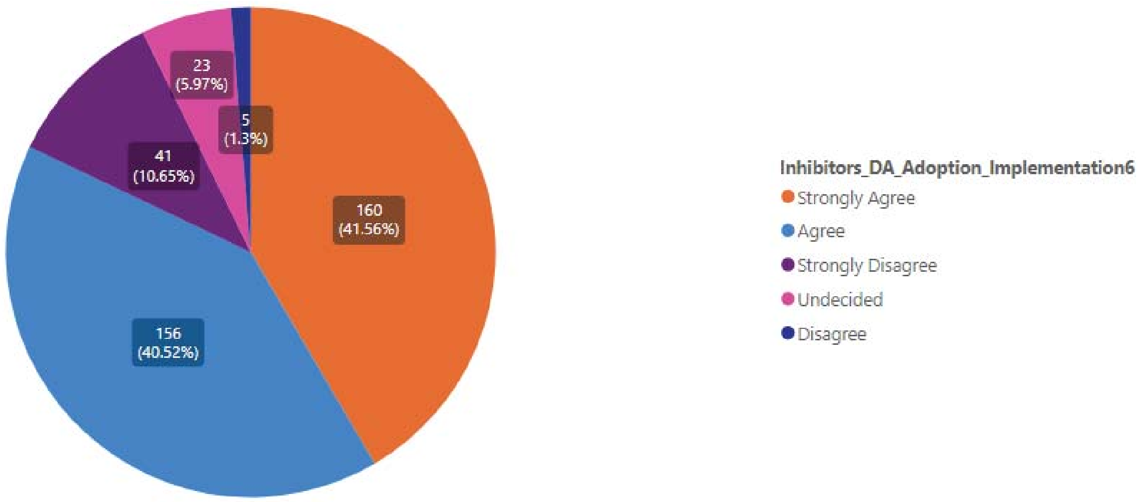

Figure 71: Inhibitors in Data Analytics Adoption/Implementation not being aware of data analytics possibilities and fail to see the value of data analytics.

Inhibitors in Data Analytics Adoption/Implementation not being aware of data analytics possibilities and fail to see the value of data analytics.	**Count**
Strongly Disagree	41
Disagree	5
Undecided	23
Agree	156
Strongly Agree	41

Table 62: Inhibitors in Data Analytics Adoption/Implementation not being aware of data analytics possibilities and failure to see the value of data analytics.

Finding: The above graph and table suggest that around 82% of the organizations believe that that lot of time the key stakeholders of the organization doesn't understand the value that data analytics can generate for the organization hence this can serve as a hindrance to the organization.

63) Inhibitors in Data Analytics Adoption/Implementation MSMEs are hesitant about the Upfront, setup, running.

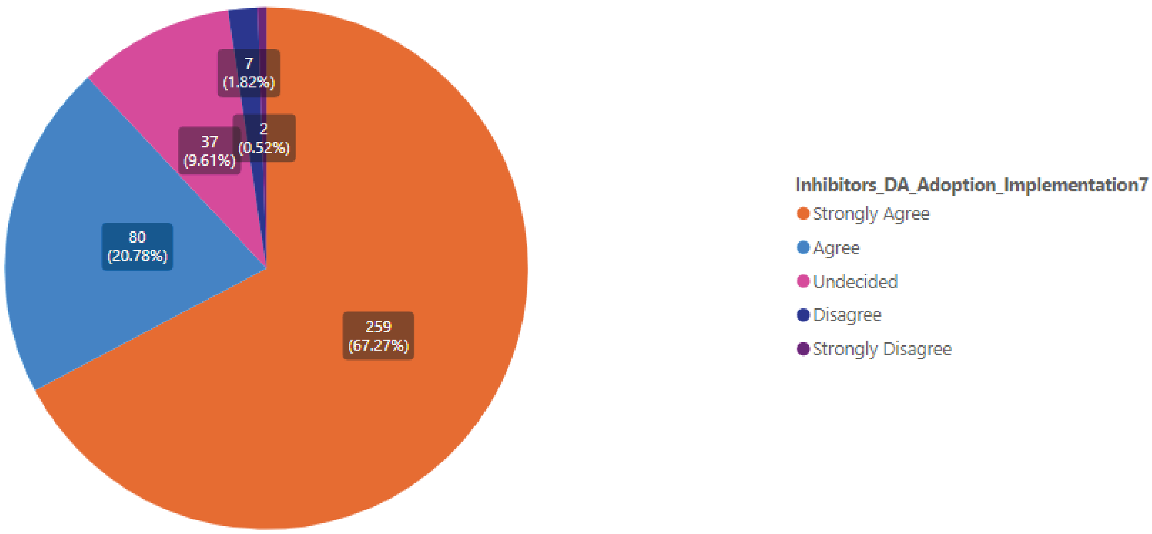

Figure 72: Inhibitors in Data Analytics Adoption/Implementation MSMEs are hesitant about the Upfront, setup, running.

Inhibitors in Data Analytics Adoption/Implementation MSMEs are hesitant about the Upfront, setup, running.	**Count**
Strongly Disagree	2
Disagree	7
Undecided	37
Agree	80
Strongly Agree	259

Table 63: Inhibitors in Data Analytics Adoption/Implementation MSMEs are hesitant about the Upfront, setup, running.

Finding: The above graph and table suggest that around 88% of the organizations believe that the initial setup required to put the data analytics practice, in reality, requires train manpower a front running cost and MSMEs are quite aware that this concern as an inhibition for the adoption or implementation of this practice.

64) Inhibitors in Data Analytics Adoption/Implementation maintenance cost of the data analytics project.

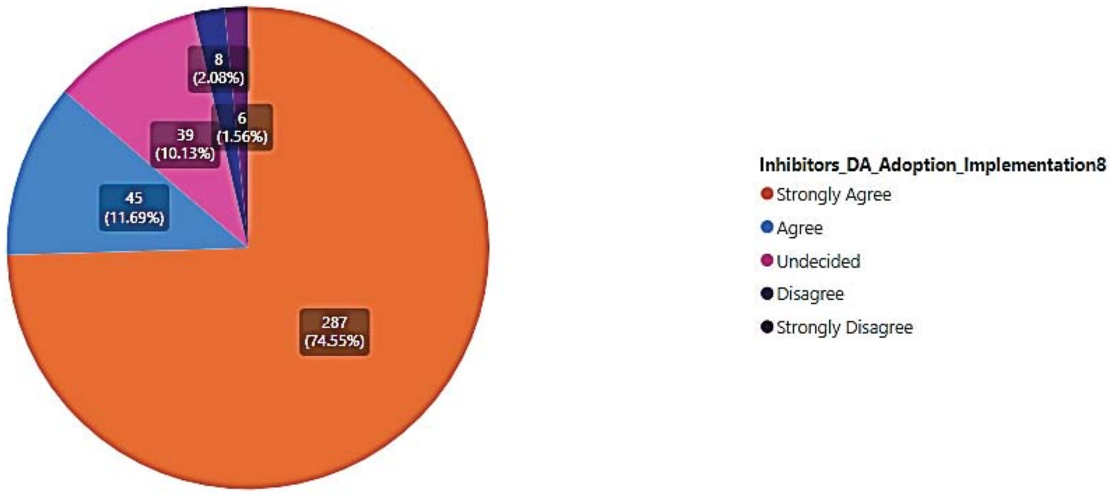

Figure 73: Inhibitors in Data Analytics Adoption/Implementation maintenance cost of the data analytics project.

Inhibitors in Data Analytics Adoption/Implementation maintenance cost of the data analytics project.	Count
Strongly Disagree	6
Disagree	8
Undecided	39
Agree	45
Strongly Agree	287

Table 64: Inhibitors in Data Analytics Adoption/Implementation maintenance cost of the data analytics project.

Finding: The above graph and table suggest that around 86% of the organizations believe that running data analytics projects and maintaining that project isa costly affair hence MSME's might think this has an inhibition while the implementation of the practice on the organizational level.

65) Inhibitors in Data Analytics Adoption/Implementation MSME's believes there is a high risk of failure and bad reputation if they go with data analytics project.

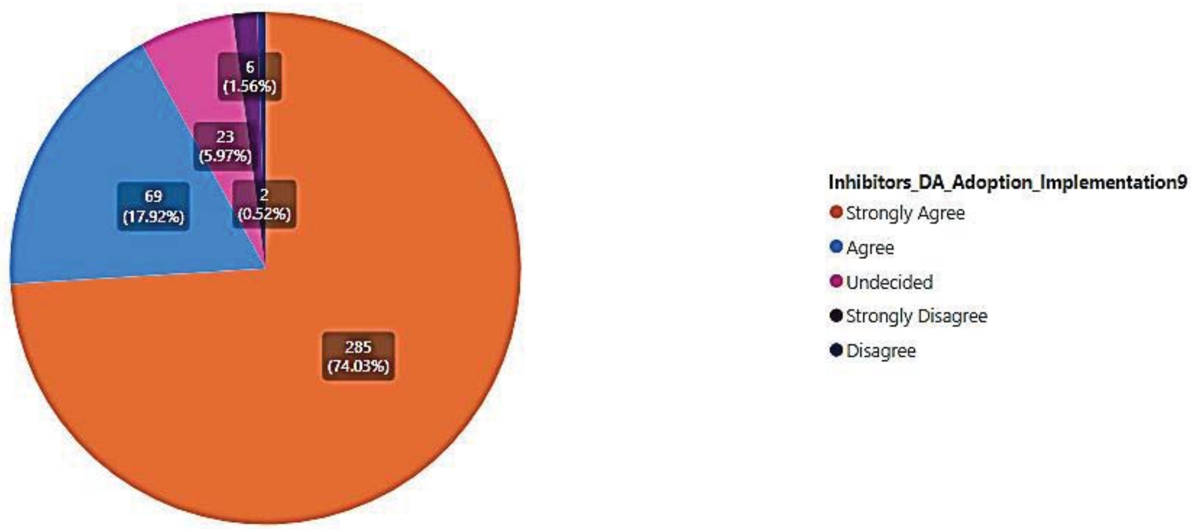

Figure 74: Inhibitors in Data Analytics Adoption/Implementation MSME's believes there is a high risk of failure and bad reputation if they go with data analytics project.

Inhibitors in Data Analytics Adoption/Implementation MSME's believes there is a high risk of failure and bad reputation if they go with data analytics project.	**Count**
Strongly Disagree	6
Disagree	2
Undecided	23
Agree	69
Strongly Agree	285

Table 65: Inhibitors in Data Analytics Adoption/Implementation MSME's believes there is a high risk of failure and bad reputation if they go with data analytics project.

Finding: The above graph and table suggest that around 92% of the organizations believe that having a data analytics project within the organization could lead to failure and will create a bad reputation in the market. The fear of this also inhibits many organisations from adopting or implementing data analytics practices.

4.2 Hypotheses Testing

Hypothesis-1

H0: There is no association between the type of business and ownership of data management software by the SME companies.

H1: There is an association between the type of business and ownership of data management software by the SME companies.

Statistical Test: Chi-square test

Level of Confidence: 0.05

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	5.874	1	.015

Table 66: Test Statistics: Evaluation of Assessment between Type of Business and Ownership of Data Management Software

Observation: $\chi^2(1) = 5.874$, $p < 0.05$

From the above observation, it is evident that the p-value is less than 0.05; hence we reject the null hypothesis, which suggests an association between the type of business and ownership of data management software by the companies. To understand the association in detail, we will follow the descriptive table given below:

Cross tabulation		**Which data management software do you have?** "Open Source"	**Which data management software do you have?** "Licensed"	**Total**
Type of business	**Manufacturing**	136	100	236
	Service	67	82	149
Total		**203**	**182**	**385**

Table 67: Crosstabulation - Use of Open-Source vs Licensed Software

The above cross tabulation table shows that manufacturing companies are using more open-source data management software, whereas service-based companies are using more licensed based data management software. To understand the viewpoint graphically, the below-mentioned bar graph will explain it:

Use of Open-Source vs Licensed Software

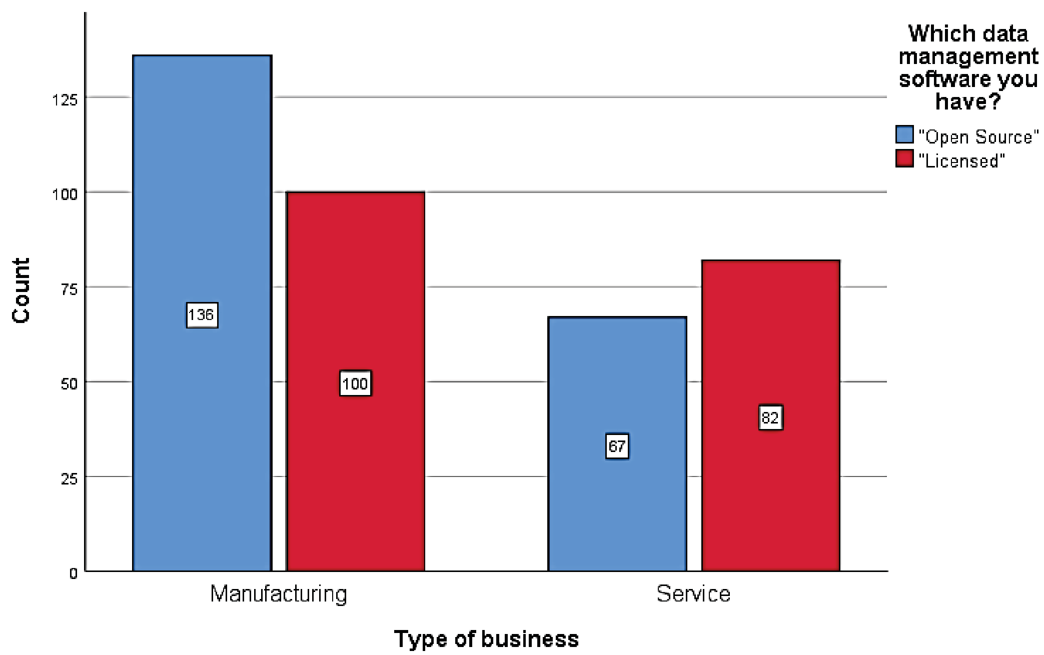

Figure 75: Crosstabulation graph of type business vs usage of open-source and licensed software

Hypothesis-2

H0: There is no association between the age of the SME company and the usage of particular data analytics service.

H1: There is an association between the age of the SME company and the usage of particular data analytics service.

Statistical Test: Chi-square test

Level of Confidence: 0.05

Test Statistics:	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	49.080	12	0.000

Table 68: Test Statistics - Evaluation of association between the age of the SME company and the usage of particular data analytics service

Observation: $\chi^2(12) = 49.080$, $p<0.05$

From the above observation, it is evident that the p-value is less than 0.05; hence we reject the null hypothesis, which suggests an association between the age of the company and the usage of particular data analytics services. To understand the association in detail, we will follow the descriptive table given below:

Type of Analysis used for Decision Making						
		Which type of Analytics is used for decision-making?				**Total**
		Descriptive	**Predictive**	**Prescriptive**	**Diagnostic**	
Time Since Establishment of Organization	**Less than 1 year**	54	18	5	11	**88**
	1 to 5 years	11	13	12	5	**41**
	6 to 10 years	10	12	22	9	**53**
	11 to 15 years	43	18	11	10	**82**
	More than 15 years	65	24	19	13	**121**
Total		**183**	**85**	**69**	**48**	**385**

Table 69: Crosstabulation of Type of Analysis used in decision making vs time of establishment of organization

From the above cross tabulation table, we can see that young companies who have just started are relying more on descriptive analytics, whereas the more mature ones focus on predictive and prescriptive analytics. Overall, companies are focusing less on diagnostics analytics. To understand the viewpoint graphically, the below-mentioned bar graph will explain it:

Time Since Establishment of Organisation vs Type of Analytic Used

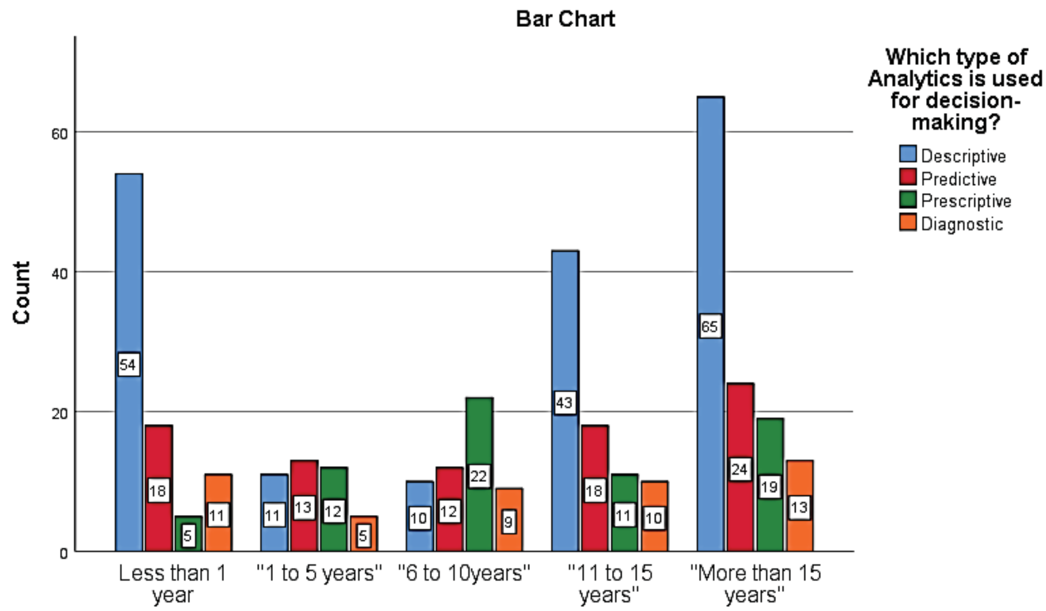

Figure 76: Crosstabulation graph of Type of Analysis used in decision making vs time of establishment of organization

Hypothesis-3

H0: There is no correlation between decision-making components that uses data analytics tools in SME's.

H1: There is a correlation between decision-making components that uses data analytics tools in SME's.

Statistical Test: Spearman Rank Correlation Test

Level of Significance: 0.05

			Data analytical tools in your organization based on Strategic decision-making	Data analytical tools in your organization based on Operational decision-making	Data analytical tools in your organization based on Tactical decision-making
Spearman's rho	Data analytical tools in your organization based on Strategic decision-making	Correlation Coefficient	1.000	.379**	-.011
		Sig. (2-tailed)	.	.000	.831
		N	385	385	385
	Data analytical tools in your organization based on Operational decision-making	Correlation Coefficient	.379**	1.000	.153**
		Sig. (2-tailed)	.000	.	.003
		N	385	385	385
	Data analytical tools in your organization based on Tactical decision-making	Correlation Coefficient	-.011	.153**	1.000
		Sig. (2-tailed)	.831	.003	.
		N	385	385	385
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 70: Test Statistics- Evaluation of correlation between decision-making components that uses data analytics tools in SME's

From the above correlation table, it is evident that strategic decision making and operational decision making are correlated to each other. Operational decision making and tactical decision making are correlated to each other. Hence strategic and tactical decision making are not correlated to each other.

Hypothesis-4

H0: There is no association between the data elements consideration as per business needs and data preparation in SME's.

H1: There is an association between the data elements consideration as per business needs and data preparation in SME's.

Statistical Test: Chi-square test

Level of Confidence: 0.05

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.804	1	.028

Table 71: Test Statistics-Evaluation of association between the data elements consideration as per business needs and data preparation in SME's

Observation: $\chi^2(1) = 4.804, p<0.05$

From the above observation, it is evident that the p-value is less than 0.05; hence we reject the null hypothesis, which suggests that there is an association between the data elements considered as per business needs and data preparation. To understand the association in detail we will follow the descriptive table given below:

		Do you prepare for data – completeness, consistency, dealing with outliers and redundant variables?		Total
		Yes	No	
Does your data is following business understanding – data elements as per business engagement points?	**No**	7	12	19
	Yes	227	139	366
Total		**234**	**151**	**385**

Table 72: Crosstabulation of Evaluation of association between the data elements consideration as per business needs and data preparation in SME's

From the above cross tabulation table, we can see that the companies that have business understanding and consider the data elements as per business engagement points prepare their respective data with completeness, consistency, and deal with outliers. To understand the viewpoint graphically, the below-mentioned bar graph will explain it:

Is your data in accordance with business understanding – data elements as per business point?

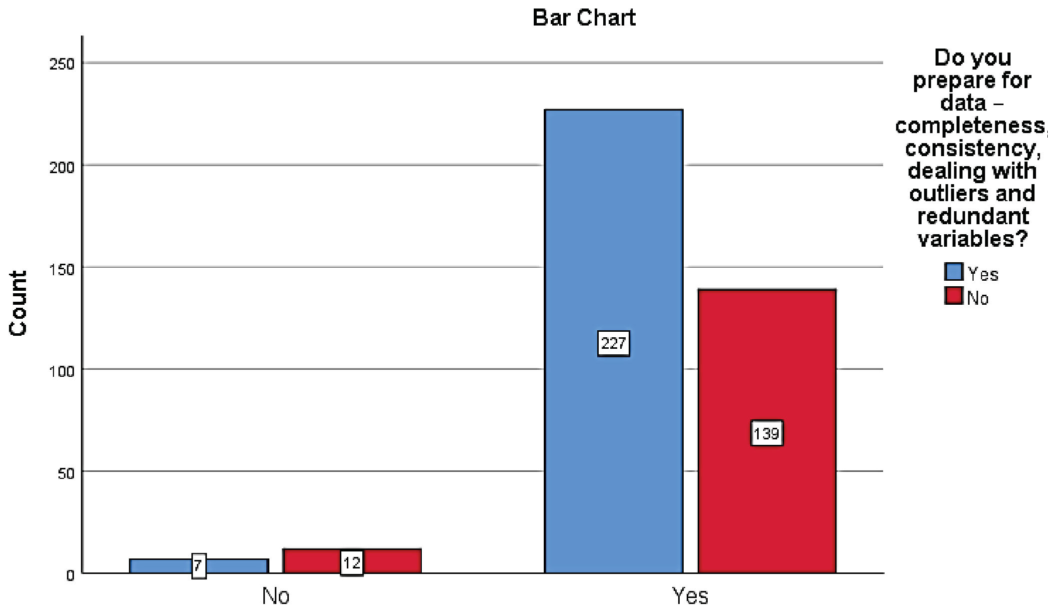

Figure 77: Crosstabulation graph of Evaluation of association between the data elements consideration as per business needs and data preparation in SME's

Hypothesis-5

H0: There is no correlation between the understanding of data analytics tools utility and the clarity about the inhibitions which can hamper the usage of data analytics tools amongst SME's.

H1: There is a correlation between the understanding of data analytics tools utility and the clarity about the inhibitions which can hamper the usage of data analytics tools amongst SME's.

Statistical Test: Pearson Correlation Test

Level of Significance: 0.05

		Inhibition Clarity	Utility Understanding
Inhibition Clarity	**Pearson Correlation**	1	.696**
	Sig. (2-tailed)		.000
	N	385	385
Utility Understanding	**Pearson Correlation**	.696**	1
	Sig. (2-tailed)	.000	
	N	385	385
****. Correlation is significant at the 0.01 level (2-tailed).**			

Table 73: Test Statistics-Evaluation of There is no correlation between the understanding of data analytics tools utility and the clarity about the inhibitions which can hamper the usage of data analytics tools amongst SME's

The above correlation table shows that the understanding of the data analytics tool's utility and the clarity about the inhibitions that can hamper the usage of data analytics tools are positively correlated. Hence, we can say that once someone understands the inhibitions, they can see the far better utility of data analytics tools for their enterprise or business.

Chapter-5 : Conclusions, Recommendations and Future Scope

5.1 Conclusions of The Research Study

The researcher has analysed the collected data and has come to the following conclusions:

1. As the researcher got to know that maximum of the sample respondents were from manufacturing SMEs as compared to the service one, the researcher concludes that most of the time, manufacturing companies have financial crunch as compared to the service companies and hence manufacturing companies prefer more open-source data analysis tools as compared to the licensed one.
2. Since the researcher has tried to understand the respondent's perception of the usage of data analytical tools in various business functions, the researcher can conclude that the companies or organisations are using data analytical practice more in sales and marketing and at the operational level more as compared to other business functions.
3. Organizations are using data analytics tools for various purposes. From the research, the researcher can conclude that majority of the organisations are using data analytics tools to understand the past data and try to predict futuristic data. However, very few organisations are leveraging advanced analytics, which talks about what to do and what not to do, which forms a part of prescription or diagnostics analytics.
4. The researcher finds that organisations use data analytics to understand the business trends and the information about their competitors. The researcher can conclude that organisations view data analysis tools as vital for solving performance problems by grasping these two things more precisely.
5. When the researcher has studied that the organisations are using data analytics services at three different levels strategic, operational, and tactical. The researcher concludes that the analytics service is more used in operational planning than the strategic or tactical. Hence, the companies use their resources more towards operations and less towards strategic or technical planning.
6. The other conclusion researcher has drawn is that if the organisations understand the business very well, which means that they know the exact engagement points which have to be studied and monitored closely, then only they will be able to capture and prepare the data with more completeness and consistency and also can take care of outliers which can

spoil the data consistency hence understanding business is closely related to capturing and preparing the data.

7. As mentioned earlier that the, organisations on an operational level majorly use the detail it takes. Still, the organisation understands that this service's utility is limited to its operations. The researcher concludes that along with functions, organisations are also leveraging this service at the strategic level to streamline the human resource requirements search as learning and development and recruitment.
8. Since the introduction of data analytics practice has changed how the businesses are functioning, the researcher concludes that because of this, organisations are adopting the change management practices on various business function levels as well as they are ready to change the business structure or for that sake the organisation type based on industry trends.
9. For any project to succeed and any organisation, the stakeholders of the organisation should understand the growth and inhibition factors. The researcher concludes that MSME' is very much aware that if stakeholders perceive data analytics service at the cost function and challenging to implement or maintain, this will create inhibition on an organisational level to adopt and implement this practice creating a competitive advantage for them.
10. Also, the researcher tried to understand the years of experience of the company or organisation and the usage of analytic services. The researcher can conclude that more mature organisations or the two young organisations less than one year focus more on descriptive or predictive analytics. In contrast, organisations that are not a decade long enough and not too young are experimenting with advanced analytics such as prescription or diagnostics analytics.
11. As the researcher has discussed above, organisations are leveraging analytics at the operational or strategic level. The researcher also concludes that if the usage of analytics at the operational level increases, it also has shown increased use of the service at the strategic level, but that doesn't mean an increase at the tactical level.
12. The conclusion that the researcher can draw from this research is that if the organisations have clarity about the inhibitions in the adoption and implementation of the data analytics practice, they will understand the utility of the service and add a much larger level; based on the previous comment, the researcher can conclude that the data analytics practice is

valuable in its own right in part because of its clarity about inhibitions and helpful format.

5.2 Recommendations Based On The Research Study

After going through so many findings and conclusions, the researcher has reached the point where the following recommendations have been put across to various stakeholders. The proposals have been mentioned below:

1) As the researcher's conclusion suggests that manufacturing organisations are using open-source software, the recommendation researcher wants to make here is if they use licensed software for their data analytics practice, they can get dedicated support from the organisations who are providing such software so that they can leverage the full potential and support for their data analytics practice.
2) The more mature and younger organisations are using descriptive or predictive analytics researcher wants to recommend here is that if these organisations use the advanced analytics which other organisations are using, which have been clear from the study also, they can benefit more from this as compared to using only or up to the certain extent the descriptive or predictive analytics hence the important should be given to the advance analytics by these organisations focusing on diagnostic or prescriptive analytics.
3) The organisations are currently focusing more on their data analytics practice on the operational level researcher wants to recommend here is that the organisation should also focus on using the data analytics service at a strategic and tactical level more because the usage of this service on all these three levels can create a sustainable and competitive advantage for the organisations considering the competition.
4) Since the researcher understands from the conclusions that importance of understanding the business is more important because only in that case the data preparation could be done better hence researcher wants to recommend that organisations should develop a learning attitude about their businesses in more detail and also they should up skill themselves in terms of understanding the data-driven culture so that the preparation of the data will happen more in line with the business points.
5) As the researcher has explained, the practical value of the data analytics practice for organisations is varied; the researcher wants to recommend here is that the organisations focus more on getting clarity by collaborating with cross-functional departments and

developing the knowledge base according to the requirement of the business as it will help them to make more informed decisions.

6) As the researcher has explained that the practical value of the analytics practices much more, the researcher wants to recommend here today's stakeholders of the organisation is that please hold the brainstorming sessions across the business functions to understand the true potential and value of the data analytics practice can deliver instead of deciding between adoption or non-adoption of analytic service into the business in isolation without consulting to the employees.

5.3 Scope For Future Research

The researcher went through various difficulties while conducting this particular research study based on the researcher's experiences in this study. The outcome of this study researcher wants to give future scope for the future researchers. They want to study the domain of this data analytics practice. The various suggestions for future results are given below:

1) A comparative study between different industries can be studied in light of data analytics practice.
2) A study can also be conducted based on the value that data analytics practice delivers to organisations.
3) A comparative study can be done for the organisations based on their software, such as open-source versus license software and business performance benefits.
4) Dedicated research can be conducted for the service industry only because there is enormous scope to cover different data points of the businesses, which are very dynamic and deliver varied benefits to the organisations.

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Questionnaire

1. Type of business (Please check (√) the option)

a. Manufacturing

b. Service

2. Year of Establishment (Please check (√) the option)

a. Less than 1 year

b. 1 to 5 years

c. 6 to 10years

d. 11 to 15 years

e. More than 15 years

3. Which data management software do you have? (Please check (√) the option)

a. **Open Source**

b. **Licensed**

4. Which Data Analytical tool/s do you use? (Please check (√) the option)

a. R Programming

b. Tableau

c. Python

d. SAS

e. Apache Spark

f. Microsoft Excel

g. Rapid Miner

h. KNIME

i. QlikView

j. Splunk

k. Others ______________________

5. To what extent does your organization use Data Analytical Tool? (Please check (√) the option) (Please check (√) the option)

a. Always
b. Sometimes
c. Once in a while
d. Rarely
e. Never

6. Please select each business function defined in the second column of the table that uses data analytical tools in your organization on a scale of 1-5

1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always.

	Purpose of data analytical tool	**1**	**2**	**3**	**4**	**5**
6.1	Sales					
6.2	Customer service					
6.3	Marketing					
6.4	Manufacturing					
6.5	Finance					
6.6	Human Resource					
6.7	Risk Management					
6.8	Learning and development					
6.9	Operations					
6.10	Other ______________________					

7. Which type of Analytics is used for decision-making? (Please check (√) multiple answers which apply)

☐ Descriptive
☐ Predictive
☐ Prescriptive
☐ Diagnostic

8. **Data Analytical tool is helpful for your Enterprise on the scale of 1-5**

1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always

		1	2	3	4	5
8.1	To understand customer patterns					
8.2	To take Business Decisions					
8.3	To Managing Relation with Third-party					
8.4	To gathering information about competitors					
8.5	Effective Data Management					
8.6	To understand business trends					
8.7	Other_______________					

9. **Is the performance of your company increased with the usage of data analytical Tools? (Please check (√) the option)**

- ☐ Strongly Agree
- ☐ Agree
- ☐ Neutral
- ☐ Disagree
- ☐ Strongly Disagree

10. **Please select the usage of data analytical tools in your organization based on decision-making categories defined in the first column of the below table in your organization.**

1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always

	Decision-making category	1	2	3	4	5
10.1	Strategic decision-making					
10.2	Operational decision-making					
10.3	Tactical decision-making					

11. For which purposes do you use data analytics tools? (Please check (√) multiple answers which apply)

- ☐ Planning (analysing data to predict market trends of products and services)
- ☐ Sourcing (procurement system, searching, negotiating and evaluating suppliers)
- ☐ Making (correct inventory and production of items in terms of time)
- ☐ Delivering (bringing products to market more efficiently)

12. Does your data is following business understanding – data elements as per business engagement points? (Please check (√) the option)

- o Yes
- o No

13. Do you prepare for data – completeness, consistency, dealing with outliers and redundant variables? (Please check (√) the option)

- o Yes
- o No

14. Please select the utility of data analytics tools that you use/have.

(1 = Strongly Disagree, 2 = Disagree, 3 = Disagree Somewhat, 4 = Undecided, 5 = Agree Somewhat, 6 = Agree, 7 = Strongly Agree).

	Utility	**1**	**2**	**3**	**4**	**5**	**6**	**7**
14.1	Allow us to select a logical choice from the available options.							
14.2	Assist us in achieving organizational or managerial objectives or goals							
14.3	Assist us in business activities – if yes list down the activities							
14.4	Validate accuracy and correctness of information							
14.5	Contribute to quality decision making							

14.6	Transformed the processes Integrated the data							
14.7	Developed skills							
14.8	Retaining experience and human resources							
14.9	Ensuring data quality							
14.10	Brought in flexible systems, collaboration, knowledge exchange, and trust and managed relationships.							
14.11	Produces near or real-time results by processing and analyzing streamed data.							
14.12	Help the business managers make informed decisions							
14.13	Help the business managers to drive the company forward,							
14.14	Help the business managers to improve efficiency							
14.15	Replaces intuition and guesswork in their decision-making							
14.16	Helps in defining the problem to be addressed							
14.17	Make decision-making more transparent, accurate, efficient, and to some extent faster.							
14.18	Has influenced the traditional roles of the individuals							

15. Data Analytics –

(1 = Strongly Disagree, 2 = Disagree, 3 = Disagree Somewhat, 4 = Undecided, 5 = Agree Somewhat, 6 = Agree, 7 = Strongly Agree).

	Data analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15.1	Has become an integral part of organizational business processes.							
15.2	Has changed the way organizations are built and function							
15.3	Lead to undergo thorough business process changes, apply change management practices for business processes.							
15.4	Brings in cost advantages to the business.							
15.5	Help businesses analyse data immediately and make quick decisions based on the learnings.							
15.6	Offers a better understanding of current market conditions.							
15.7	Help organizations to create new growth opportunities and entirely new categories of companies that can combine and analyse industry data.							
15.8	Understands and optimizes business processes.							

16. Inhibitors in Data Analytics Adoption/Implementation –

(1 = Strongly Disagree, 2 = Disagree, 3 = Disagree Somewhat, 4 = Undecided, 5 = Agree Somewhat, 6 = Agree, 7 = Strongly Agree).

	Data analytics	**1**	**2**	**3**	**4**	**5**	**6**	**7**
16.1	Without good data quality, the trust in data analytics projects suffers.							
16.2	Data quality is low, and the users do not trust the data, decision-making could be taken out of false promises.							
16.3	MSMEs lacks financial strength, has tight budgets.							
16.4	There is a lack of sponsors to have the money for Data analytics project implementation.							
16.5	There is a lack of experience and understanding possibilities amongst MSME.							
16.6	Not being aware of data analytics possibilities and failure to see the value of data analytics.							
16.7	MSME's are hesitant about the Upfront, setup, running, and maintenance cost of the data analytics project.							
16.8	MSME's believes there is high risks of failure and a bad reputation if they go with data analytics project.							