2022

DATA ANALYTICS FOR CRISIS MANAGEMENT: A CASE STUDY OF SHARING ECONOMY SERVICES IN THE COVID-19 PANDEMIC

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DATA ANALYTICS FOR CRISIS MANAGEMENT: A CASE STUDY OF SHARING ECONOMY SERVICES IN THE COVID-19 PANDEMIC

by

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A Dissertation

Presented to the Long Island University

in

Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

October 2022

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ACKNOWLEDGMENTS

I would like to thank my family, for giving me support and patience throughout the doctoral journey. I want to offer my gratitude to my friends for being supportive and helpful throughout my studies.

I am indebted to all my teachers at Istanbul Technical University, New York Institute of Technology, Stony Brook University, and Long Island University. I extend a special thanks to Dr. Beatrice Baaden, Dr. Heting Chu, Dr. Gregory Hunter, Dr. David Jank, Dr. Stephanie White, and Dr. Qiping Zhang for teaching us how to be a scientist. I also thank our doctoral colleagues for providing support.

The COVID-19 pandemic started in the early phases of my doctoral journey. A special thanks to my advisors Dr. Chu and Dr. Beatrice Baaden, and my external advisor Dr. Alireza Ebrahimi, Dr. Selenay Aytac, Dr. Mary Westermann, and Dr. Sevil Oztimurlenk for supervision and guidance. I truly appreciate your feedback and time. An extra special thanks to Ian and Ron, two of my fellow librarian friends at Westbury Library, where I finished my study. I was able to navigate the research on the proper path thanks to their recommendations.

Lastly, I would like to thank the faculty and staff of Long Island University for their hard work and assistance. My doctoral journey couldn't have been completed without the help of the registrar's and financial aid office. I also acknowledge that we are a big family, with memories to last a lifetime.

DEDICATION

I dedicate my dissertation work to my family, teachers, and friends. A special feeling of gratitude to my brother and my sister raised me and became role models growing up.

I dedicate this dissertation to my bachelor's degree senior project advisor, Michael Madigan, who helped me to graduate with a very difficult project. He was always patient and helpful. We lost him in a car accident a few years ago. The New York Institute of Technology community will miss him.

I also dedicate this work to all my teachers and professors at Long Island University, for their hard work, patience, and encouragement.

Finally, I dedicate this study to Professor Peter Carr, who passed away suddenly earlier this year. He was one of the greatest quants that can work on the derivatives with scientists all over the world and was always happy and smiling. New York University community will miss him.

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ABSTRACT

This dissertation study aims to analyze the role of data-driven decision-making in sharing economy during the COVID-19 pandemic as a crisis management tool. In the twenty-first century, when applying analytical tools has become an essential component of business decision-making, including operations on crisis management, data analytics is an emerging field. To carry out corporate strategies, data-driven decision-making is seen as a crucial component of business operations. Data analytics can be applied to benefit-cost evaluations, strategy planning, client engagement, and service quality. Data forecasting can also be used to keep an eye on business operations and foresee potential risks. Risk Management and planning are essential for allocating the necessary resources with minimal cost and time and to be ready for a crisis. Hidden market trends and customer preferences can help companies make knowledgeable business decisions during crises and recessions. Each company should manage operations and response during emergencies, a path to recovery, and prepare for future similar events with appropriate data management tools. Sharing economy is part of social commerce, that brings together individuals who have underused assets and who want to rent those assets short-term. COVID-19 has emphasized the need for digital transformation. Since the pandemic began, the sharing economy has been facing challenges, while market demand dropped significantly. Shelter-in-Place and Stay-at-Home orders changed the way of offering such sharing services. Stricter safety procedures and the need for a strong balance sheet are the key take points to surviving during this difficult health crisis. Predictive analytics and peer-reviewed articles are used to assess the pandemic's effects. The approaches chosen to assess the research objectives and the research questions are the predictive financial performance of Uber & Airbnb, bibliographic coupling, and keyword occurrence analyses of peer-reviewed works about the influence of data analytics on the

sharing economy. The VOSViewer Bibliometric software program is utilized for computing bibliometric analysis, RapidMiner Predictive Data Analytics for computing data analytics, and LucidChart for visualizing data.

Keywords: Airbnb, Bibliometric Analysis, Bibliographic Coupling, Black Swan, COVID-19, COVID-19 Pandemic, Crisis Management, Data Analytics, Data-Driven Decision Making, Predictive Analytics, Risk Management, Sharing Economy, Systemic Risk, Uber, Value at Risk, Visualized Bibliometric Mapping

CHAPTER 1 INTRODUCTION AND BACKGROUND

Data analytics is an emerging field in the twenty-first century when using analytical tools has become a fundamental part of the business decision-making process, including operations on crisis management. The exponential growth of data, with technological advancement, inspires the creation of devices such as smartphones and the development of space technologies. As a result, the amount of information generated from these devices and technologies is surging, leading to the so-called big data, which has become a disruptive element in the workforce. Data analytics has been demonstrated to be an asset to identify patterns, predicting outcomes, and guiding corporate strategies (Ngai, Xiu, and Chau 2009). Data-driven decision-making is observed as an essential part of business operations. It is achieved by extracting descriptive insights to observe current operations, predictive insights to forecast possible future events, and prescriptive insights to execute business strategies (Hair 2007). Effective planning is a critical factor for allocating the necessary resources with minimal cost and time. The indicators that are gathered from the computational models are part of the crisis and risk management to be ready for any outcome. These insights can show an upcoming systemic risk, such that allocating resources to avoid these downturns or delay the losses.

The adoption of mobile technology, corporate downsizing, automation, the emergence of technologically empowered business platforms, and the growth of the millennial population are the main factors for our society's shifting toward the sharing economy (Manning et al. 2018). The sharing economy is part of social commerce, where the part-time work model is the norm. It is built on online marketplaces that connect those who seek to rent out short-term, underutilized assets (Cusumano 2015). The cost of economic coordination dropped significantly as a form of commerce that is mediated by social media. There is a consistent outgrowth of social media platforms where companies can expand their potential markets by renting access to products that people used to buy. The economic model is peer-to-peer (P2P) access that provides temporary access to underutilized goods and services (Stanoevska-Slabeva et al. 2017). The service technology platform involves the sharing of physical assets and services among people. These platforms are based on the P2P interaction between the customer and company, where each operation is part of the facilitation process. Social interaction is the norm for these services. Demand and supply market setting determines the prices. Ride-hailing apps (e.g., Uber), and home-sharing services (e.g., Airbnb) are the main businesses of the sharing economy (Nichol 2016).

Sharing economy technology platforms collect information through various channels to optimize their services. The development of information technologies and social media technologies promotes community-based online services (Hamari, Sjoklint, and Ukkonen 2016). Social commerce relies on the platform with P2P interaction with the motivation of users to continue participation. COVID-19 has emphasized the need for digital transformation. Companies should manage operations and response during crises, a path to recovery, and prepare for future similar events with appropriate data management tools. They are expected to navigate their tasks with the ability to derive insights and determine the critical factors for their crisis management strategy.

The sharing economy has become a trend where the business model is transforming into a just-in-time model that adds job tasks while each employee has been assigned them. The system model represents the allocation and organization of resources. New technologies disrupt and transform this model with a collaborative ecosystem, as well as an agile and adaptive organization. The transactional framework is the foundational basis where the service is required as needed based on asynchronous settings (Henten and Windekilde 2016). A business model is a system whose various features determine the success level with each reaction. Each transaction is linked with customer and user ratings that are linked to data analytics that affects business operations. The cost-benefit analysis depends on the accessibility of the application portal and the quality of the services they offered on their platform (Wang et al. 2017). Profit and loss optimization is critical during a crisis for offering quality services. Each company can offer its services to consumers when the financial balance sheet is healthy and allocate the resources when it is required.

Home-sharing services are part of the hospitality exchange services, where the exchange of accommodation occurs via social interaction (Ikkala and Lampinen 2015). The host and guests are part of this transactional hospitality space. This interaction includes offering accommodation, food, and expressions of gratitude. The idea of renting free space in one’s apartment or house is the main idea of Airbnb, which was originally called Airbed & Breakfast, and started as an Internet company in August 2008 (Aydin 2019). The founders of Airbnb established a technology platform that introduces a new business model that would challenge the traditional hotel business in 2008 (Kavadias, Ladas, and Loch 2016). The online platform matches travelers who are looking for accommodation with homeowners willing to share a room or house, where Airbnb takes a percentage of the rent. Its philosophy is based on the regulated lower prices due to not owning or managing physical assets, with a more personal and diversified service. Accommodation was one of the most important factors during the pandemic, with stay-at-home orders and remote-work procedures. Airbnb is the ideal way to observe how data analytics can be implemented during a crisis for accommodation.

Uber was introduced as a transportation network and logistics service company in 2009 (Anwar 2018). Its core value is a reduction of search and transaction costs for both drivers and passengers (Blystone 2020). The cost of transportation is the only cost to be considered, as all economic agents know the prices of all possibilities of services. The rating system allows the customers to see on mobile devices of the closest driver and their ratings (Kavadias, Ladas, and Loch 2016). The platform is established to offer convenient and personal hailing services, unlike traditional taxi services. The maximization of driver earnings and the optimization of passenger demand is linked with economic pricing and the minimization of travel time (Chaudhari et al. 2018). Uber is a great crisis management case study where data analytics is used during the pandemic for more efficient and safe services.

Since the COVID-19 pandemic began, the sharing economy has been facing challenges. The market demand for ride-hailing and home-sharing services dropped significantly (Hossain 2021). Millions of people in the sharing economy services lost their jobs when the pandemic began. Uber's rides declined 80 percent in April 2020, and Airbnb bookings were down 18 percent nationwide in December 2020 (Conger 2021). Shelter-in-Place and Stay-at-Home orders changed the way of offering such sharing services. People moved out of big cities and relocated to the suburbs. There was an important drop in traveler statistics for using ride-hailing and home-renting services. Customer confidence was correlated with the demand for lodging and shared transportation (Batool et al. 2020). During the COVID-19 pandemic, customer engagement is based on improved safety standards, social distancing, mask usage, and disinfecting of the area where the service occurs. Stricter safety procedures and the need for a strong balance sheet are the key take points to surviving during this difficult health crisis. The challenges include the worker's status and benefits and new customer offerings in such services.

This research investigates the role of data analytics in crisis management for sharing economy services during the COVID-19 pandemic. The manageability of the crisis is based on handling the measures in gaining customers' confidence, implementing the safety protocols to slow the transmission of the virus, developing insurance policies, and treating service personnel as employees for better business practices, and effective business operations with customer satisfaction as a top priority. The data analytics can be used as indicators of service quality, customers' engagement with the shared economy platform, benefit-cost analyses, and strategic planning based on crisis management. The information generated from data analytics reveals hidden market trends and customer preferences that can help companies make knowledgeable business decisions during crises and recessions. It is historically proven that data analytics is a crucial factor in implementing business operations. The businesses will have problems day-to-day studying their system without such displays of facts for a quicker timeline and an inexpensive price range. The research findings are limited to analyzing the function of data-driven decision-making as a crisis management tool during the pandemic while applying computational suites for predictive data analytics. The research results are meant for attaining the dissertation study objectives.

1.1 DATA ANALYTICS AND ITS FUNCTIONS

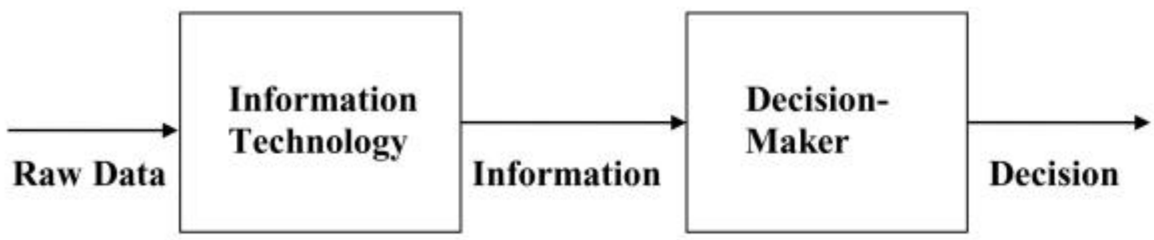
Data analytics is a set of analytical and functional tools to gain insights into business processes and uncover hidden patterns from the business intelligence view. It is the use of data, obtained from different sources, via statistical and quantitative analysis, explanatory and predictive models, and fact-based management to guide the decision-making and activities of the stakeholders (Davenport and Harris 2007). It is a collection of theories and technologies that turn raw data into relevant and usable information for day-to-day operations, based on the analysis of datasets to deduce the information found within them. Some business questions can be answered to find potential prospects that will give a company a competitive edge in the market. These are "what happened?" in a descriptive sense, "why did it happen?" in a diagnostic sense, and "when might it happen?" in a predictive sense (Chartered Global Management Accountant 2016). These questions can be grouped as below:

TABLE 1.1: STRUCTURE OF BUSINESS QUESTIONS CATALOG (NALCHIGAR AND YU 2018)

Question Type	Question Tense		
	Past	Present	Future
What	**What happened?**	**What is happening?**	**What will happen?**
	What was total sales amount for last year? * What promotion channel had highest click rate? *	What products are often purchased together? * What is the optimal order size for each product? **	What will be return to equity (ROE) in next quarter? ★ What will be the next purchase of a given user? ★
Who	**Who was involved in it?**	**Who is involved in it?**	**Who will be involved in it?**
	Who were the most impulsive buyers? * Who were promoted in last fiscal year? *	Who are the most active online users? * Who (employees) are top performers? *	Who (customers) will terminate the subscription? ★ Who will be clicking on the marketing email link? ★
When	**When did it happen?**	**Is it happening now?**	**When will it happen?**
	When (season) did we have maximum sales? * When most employees left the firm? *	Is the current credit card transaction a fraud? ★ Is the current user review a negative sentiment? ★	When will software outage happen? ★ When will each user most probably open the app? ★
Where	**Where did it happen?**	**Where is it happening?**	**Where will it happen?**
	Where (warehouses) did we have minimum waste amount? *Where (store locations) had maximum sale? *	Where (geospatial points) have the most rainfall? *Where (city areas) are similar in housing values? *	Where (province) will have maximum online visit? ★Where will most likely each customer group shop? ★
Why	**Why did it happen?**	**Why is it happening?**	**Why will it happen?**
	Why store sales were below the target? Why did the marketing campaign perform well?	Why is there a decreasing trend in website traffic? *Why visit session ends after a certain click? *	Why will a given product be of interest to a customer? ★ Why will a certain customer churn? ★
How	**How did it happen?**	**How is it happening?**	**How will it happen?**
	How was the overall ratings in user reviews? * How effective was the new website map? *	How frequent on average a user visit the website? * How is the new promotion impacting total sales? *	How long will the current visit rate Continue to grow? ★ How will new supply policy impact product levels? **

As seen in the table above, the questions are a step-by-step method that uses sophisticated analytical methods to add an extra layer of strategic efficiency to corporate planning. To explain questions and aid decision-making, the original data is processed using advanced computer systems and translated into various formats and classifications of critical information. The information tells the tale of a company's activities and success. The transformed data will assist organizations in making more educated and strategic decisions by identifying important factors. Data analysis is an important job to solve problems for businesses. The model below how raw data is processed by existing technologies to gather insights for effective business operations:

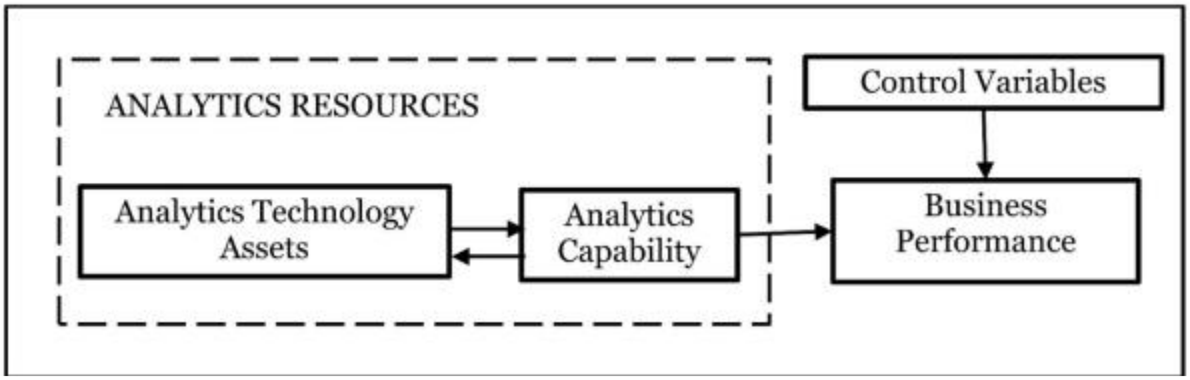
FIGURE 1.1: INPUT-PROCESS-OUTPUT MODEL FOR INFORMATION SYSTEMS (NAJDENOV AND MAKHOUL 2015)



As seen in the figure above, data scientists process raw data using Information Technology to create insights for the decision-makers to evaluate a suitable business strategy. Raw data is processed with computational operations to gather analytical intelligence. Businesses use data analytics to improve their sales and operations. It enables managers to comprehend the complexities of business procedures and handle risks, allowing companies to make faster and more informed decisions while also providing a competitive advantage through the scientific method for translating data into insights for better decision-making (Vidgen, Shaw, and Grant 2017). Data-driven organizations have higher operating performance, higher customer satisfaction, and optimal profit-to-revenue ratios. Streaming data from information sources and social media platforms are the main consideration for data analytics (Bartosik-Purgat and Ratajczak-Mrożek 2018). It is done by empowering them to make customer-centric marketing choices that will assist them in addressing key factors that will help them enhance service. Data governance over its lifecycle, data analytics to turn data to meet business needs, and data visualization to reflect data in several visual ways to illustrate patterns and trends to help business decision-making are all covered by the data analytics competency (Monterio 2019). Product innovation and workforce planning both provide key success indicators. By using data analytics as an enterprise-wide solution, businesses can improve their ability to calculate, assess, and manage risk. Organizations use data analytics to enhance risk prevention by using variables such as the use of people, processes, frequency of time, and rate of success (Taylor et al. 2017). Business managers must define risks and rewards when managing and modifying current business models and incorporating analytics into their operations. Data-driven planning based on analytics is an integral part of crisis management, where each decision is critical to the survival of each organization. This functionality is extremely beneficial to sharing economy services in terms of optimizing their business planning. Since the start of COVID-19, Uber and Airbnb have made significant commitments to their operations based on key performance metrics.

Proper risk management is critical for each company during difficult times. Analytics can be used to manage business continuity and retention by monitoring, forecasting, and preparing for crisis management and incorporating them into the strategy (Radwan 2006). The decision-making process is an important aspect of business that affects economic development and the long-term viability of the world in which they live. The figure below describes the linkage between the analytical capability of a company and business performance:

FIGURE 1.2: THEORETICAL FRAMEWORK FOR BUSINESS VALUE OF BUSINESS ANALYTICS (KRISHNAMOORTHI AND MATHEW 2018)



As seen in the figure above, an organization's technology assets determine its analytics capabilities. State-of-the-art technology affects business performance by using some control variables that can be executed during operations. Technical capability competency, proper infrastructure, efficient data life cycle management, built-in continuous feedback, and user education are the foundations for a wide range of analytics applications and capabilities (Deloitte 2015). The suggested improvements point to a closer look at how analytical methods are integrated into the execution and linked to every level of corporate planning. The semantics structure that manages data extraction and data quality is the foundation for the scalability of corporate planning using these tools (Taylor et al. 2017). In the processes and techniques, machine learning algorithms and simulation may be used. The important steps are deciding on grouping criteria, collecting, arranging, and cleaning. Each step is linked to the quality of the data and the purpose that is to be simulated.

There are three different kinds of data analytics with different purposes and each stage increases in complexity. Descriptive analytics is a form of analytics that defines events over time. Predictive analytics focuses on the cause of any occurrence by making hypotheses based on a variety of datasets. Prescriptive analytics denotes a technique for intervention.

Descriptive analytics uses methods and statistics to explain and identify a problem's current state (what happened? or what is happening?). In unpredictable times, descriptive analytics allows businesses to better sense opportunities (Akter et al. 2019). It lays the groundwork for converting data into facts – a look back at what happened. Offering input into what has happened in their internal and external environments, helps companies to understand, filter, form, and calibrate opportunities. Responding to the changing environment improves the organization's internal processes. During COVID-19, this is a crucial aspect to consider when analyzing current events and situations.

Organizations can take advantage of opportunities by transforming processes and improving cost-benefit analysis with predictive analytics (Jeble, Kumari, and Patil 2018). This collection of tools is used to create business practices and dynamic reports, as well as to provide insight into a particular issue. It describes a phenomenon that has occurred in the past. It offers advanced predictions as well as the ability to model future results and outcomes – the ability to gain insight into current processing. Making predictions enhances risk management in the business. utilizing past information to forecast future tendencies. Predictive approaches can be used to assess the issues and difficulties with the sharing economy during COVID-19, and decisions can be taken based on projected scenario analyses.

Prescriptive analytics is a branch of data analytics that focuses on determining the best course of action in each situation based on the data available (Rijmenam et al. 2019). This process includes the items that are known about the data, the decision itself, and the expected outcome of the decision. It interprets data and recommends actions using machine learning techniques and dynamic rule engines – the foresight view of what to expect and what to do next for an actionable suggestion about how to proceed (Hair 2007). Data processing techniques and algorithms, along with analytics forecasting and modeling capabilities, are used to increase business performance. Suggested best-case and worst-case scenarios can be tested during COVID-19 to construct a secure and productive work atmosphere. Prescriptive analytics is the next step in the planning process, and it is the most developed of the three. Each cooperative strategy and forecast outcome based on market scenarios visualized using a model of data analytics improves the level of knowledge sharing (Ghasemaghaei 2019). It is a vital part of the effective and stable operations for crisis management during COVID-19 to disseminate information and acquired knowledge.

The use of business analytics in a data-driven setting shows that there is a way to enhance management capability by offering valuable insights (Cao, Duan, and Li 2015). These observations will pave the way for a good business strategy that puts them ahead of the competition. Because of advancements in information technology, data analytics has enabled service technology systems to create innovative ways to respond to customer needs. Since sharing economy providers must invest in technology infrastructure to work, a data analytics approach to crisis management allows for dynamic capabilities to adapt to changes. Most business analytics activities are focused on descriptive analytics for diagnosing issues and predictive analytics for forecasting (Larose and Larose, 2015). This research aims to adopt a predictive data analytic approach to examining the role of data analytics for crisis management in the cases of Uber and Airbnb.

1.2 COVID-19 PANDEMIC AND CRISIS MANAGEMENT IN SHARING ECONOMY

As of Oct 15th, 2021, there have been more than 239 million cases of COVID-19 (World Health Organization 2021). World Health Organization (WHO) was informed of cases of pneumonia with unknown causes on December 31, 2019, and in March 2020 WHO declared that

COVID-19 was a pandemic (Cucinotta and Vanelli 2020). The rapid spread of the disease eventually brought many countries to a stands-still, including the closure of all public-facing services such as home-sharing and ride-hailing.

Although the main emphasis is on containing and mitigating the disease itself, companies need to establish a corporate plan for unanticipated business risks and downturns. Crisis management should be based on real-time analytical insights based on experts' knowledge and forecasting of what is happening and what could happen (Reeves, Lang, and Carlsson-Szlezak 2020). Consistent communication with the employees and consumers is part of establishing resilience principles in developing policies. Computing technologies may also help with supply chain management and workforce continuity (Shah and Shah 2020). The procedures include preparing the appropriate measures, developing smart preventive capabilities rather than isolation, and innovating privacy-preserving contact tracing, which detects the names of those who were near the infected person during the relevant time frame without gaining access to their comings and goings and planning based on data-driven dynamic risk assessment.

Even though sharing economy services are seen as a transformative business innovation model (Ritter and Schanz 2019), COVID-19 resulted in cancellations, job losses, and pay cuts, as well as safety and health issues for workers and customers (Hossain 2021). Sharing economy services were affected as a stage that needs to be revamped to be effective. Travelers were afraid of using Uber rides or Airbnb bookings. Drivers were afraid to drive and room owners were hesitant to rent. Transparent and clear policymaking was needed for each company to cope with the pandemic, as well as slow the transmission of the disease. Data analytics can play a major role in developing such guidance. Significant insights, key safety initiatives based on contact tracing, finding the correct service form based on feedback, and implementing required decisions for secure and productive business operations can all be determined using a predictive analytics approach.

COVID-19 is a macroeconomic shock that alters fundamental macroeconomic variables and relationships, having a significant impact on macroeconomic outcomes and performance measures (Dolnicar and Zare 2020). Transportation and lodging are two of the most critical sectors of the sharing economy in terms of everyday use, and they are affected by this macroeconomic downturn. The decline in ride-hailing and home-sharing services are due to in place, online education, and work-from-home policies. Uber and Airbnb services are part of our daily lives to get tasks accomplished. We need to get to work or places by using Uber ride-hailing services or renting a room on Airbnb for accommodation. They also complement the economy while creating new employment opportunities.

The travel and tourism enterprise's global sales become dropped by about forty-two percent in 2020 (Statista 2020, under "Forecasted Change in Revenue from the Travel and Tourism Industry due to the Coronavirus (COVID-19) Pandemic Worldwide from 2019 to 2020 (in million U.S. dollars)”). This had a disruptive effect on the company. Due to the COVID-19 epidemic, Airbnb has lost about 4.5 billion dollars (Statista 2021, under “Net loss of Airbnb worldwide from 2017 to 2020”). During the pandemic, hosts who rely on Airbnb for income are having financial difficulties paying their bills. Both occupancy and average daily rates dropped further in the short-term rental industry (Lane 2020). Throughout the pandemic, Airbnb laid off twenty-five percent of its workers, or around 1900 of its 7500 staff, and agreed to halt operations that did not explicitly serve the center of its host group (Statista 2020, under "Forecasted Change in Revenue from the Travel and Tourism Industry due to the Coronavirus (COVID-19) Pandemic Worldwide from 2019 to 2020 (in million U.S. dollars)”). More than seventy percent of guests are afraid to stay at an Airbnb venue, while forty-seven percent of hosts do not feel comfortable renting to them. There is an increase of guess cancellations up to sixty-four percent resulting in a forty-four percent drop in sales. With an average loss rate of $4000, forty-five percent of hosts were unable to sustain operating costs after just six months (Statista 2020, under "Forecasted Change in Revenue from the Travel and Tourism Industry due to the Coronavirus (COVID-19) Pandemic Worldwide from 2019 to 2020 (in million U.S. dollars)”).

As compared to annual bookings in 2019, ride-hailing trips and gross bookings are down by up to seventy-five percent (Bello and Rana 2020). From April to June 2020, the corporation suffered a net loss of 1.8 billion dollars, resulting in the layoff of twenty-three percent of its global workforce. In the second quarter of 2020, fifty-five million people used the Uber app every month, which was a forty-six percent decrease compared to the first three months of 2020 (Statista 2020, under “Monthly Number of Uber's Active Users Worldwide from 2017 to 2020, by quarter (in millions)”). In the United States and Canada, Uber's ride-hailing segment shrank to 1.25 billion.

These statistics show that the demand for shared economy services is much lower than in the previous year 2019 because of COVID-19 and effective decision-making is required to cope with the decreased demand to maintain survivability. A predictive analytics approach can help with crisis management in the sharing economy during the pandemic. This proposed dissertation research aims to investigate the role of data analytics in shared economy services during the COVID-19 pandemic with references to Airbnb and Uber. The proposed study will conduct a qualitative and quantitative analysis of selected scientific articles on crisis management of sharing economy, keywords, and relevant financial data about Uber and Airbnb. The financial aggregate predictive modeling and thematic coding scheme based on bibliographic coupling and keyword analysis will be created. The comparative quantitative data model and the bibliographic coding data model will be analyzed to investigate the role of data analytics in sharing economy during the COVID-19 pandemic.

1.3 OPERATIONAL DEFINITIONS FOR THE DISSERTATION STUDY VARIABLES

In the dissertation study, the operational definition of the following variables—the economic data, the trend data, and the action process factor—is examined. The economic information provides historical stock performance statistics for Uber and Airbnb during the COVID-19 pandemic. The trend data is an evaluation of the relationship between the sharing economy, crisis management, and data analytics during the COVID-19 pandemic based on bibliographic coupling and keyword analysis. The holistic perspective of recommendations to improve these services' data analytics capabilities for risk management preparation is the active process aspect.

1.4 DEFINITION OF RESEARCH TERMINOLOGY

These are the terminologies that were discussed, cited, and analyzed:

Black Swan: A black swan is an unforeseen occurrence that goes beyond what is expected in a circumstance (The Investopedia Team 2022). These events are frequently not predicted utilizing forecasting modeling and procedures, where they might have significant negative consequences on economies.

COVID-19 Disease: The infectious disease known as coronavirus disease (COVID-19) is caused by the SARS-CoV-2 virus (World Health Organization 2022). Infected individuals will develop a mild to a severe respiratory condition, but they will recover without the need for special treatment. The best way to stop the spread of the disease is to educate yourself about it.

Crisis Management: Crisis management is known as strategy building and making plans to address crises (Hayes 2022). Risk analysis is the first step in crisis management, which is different from risk management. Organizations and countries need to be ready for catastrophic events to survive. It is identifying potential factors that cause harmful occurrences and computing the likelihood risk to be ready. The COVID-19 situation is an example of a crisis management study.

Data Analytics: It is the study of unprocessed data to draw assumptions about such information (Frankenfield 2022). Data Analytics techniques can compute trends and indicators to assist decision making

Data-Driven Decision-Making: Data-driven decision-making is the process of making organizational decisions that are informed by data rather than mere intuition or observation (Miller 2019). The necessary steps are identifying data sources, organizing and cleaning up data, and drawing findings from statistical analysis.

Heavy-Tailed Data: Heavy-tailed distributions have a significant likelihood that an unexpected event would occur (Statistics How To 2022). Compared to an exponential distribution, a heavy-tailed distribution has a heavier tail.

Predictive Analytics: To determine whether data trends tend to repeat themselves, predictive analytics evaluates both historical and current data trends (Halton 2021).

Regression Analysis: Regression is a statistical technique that links a dependent variable to one or more independent (explanatory) variables (Beers 2022). A regression model can demonstrate whether changes in one or more of the explanatory variables are related to changes in the dependent variable. This is achieved by essentially fitting a best-fit line and observing the distribution of the data around this line.

Risk Management: Risk management is the detection, analysis, and reaction to risk elements in a business's operations (CFI Team 2022). Good risk management is about acting proactively about future events to lessen both the likelihood of a risk happening and its possible consequences. Risk Management steps are identifying the uncertainty, assessing, and controlling it with preventive steps, as well as reviewing the security protocols.

Sharing Economy: Sharing economy is an online marketplace that connects consumers and sellers (The Investopedia Team 2020). Sharing economies make it possible for individuals and businesses to profit from unused resources. In a sharing economy, empty spaces, such as parked cars and additional beds, can be rented out while not in use.

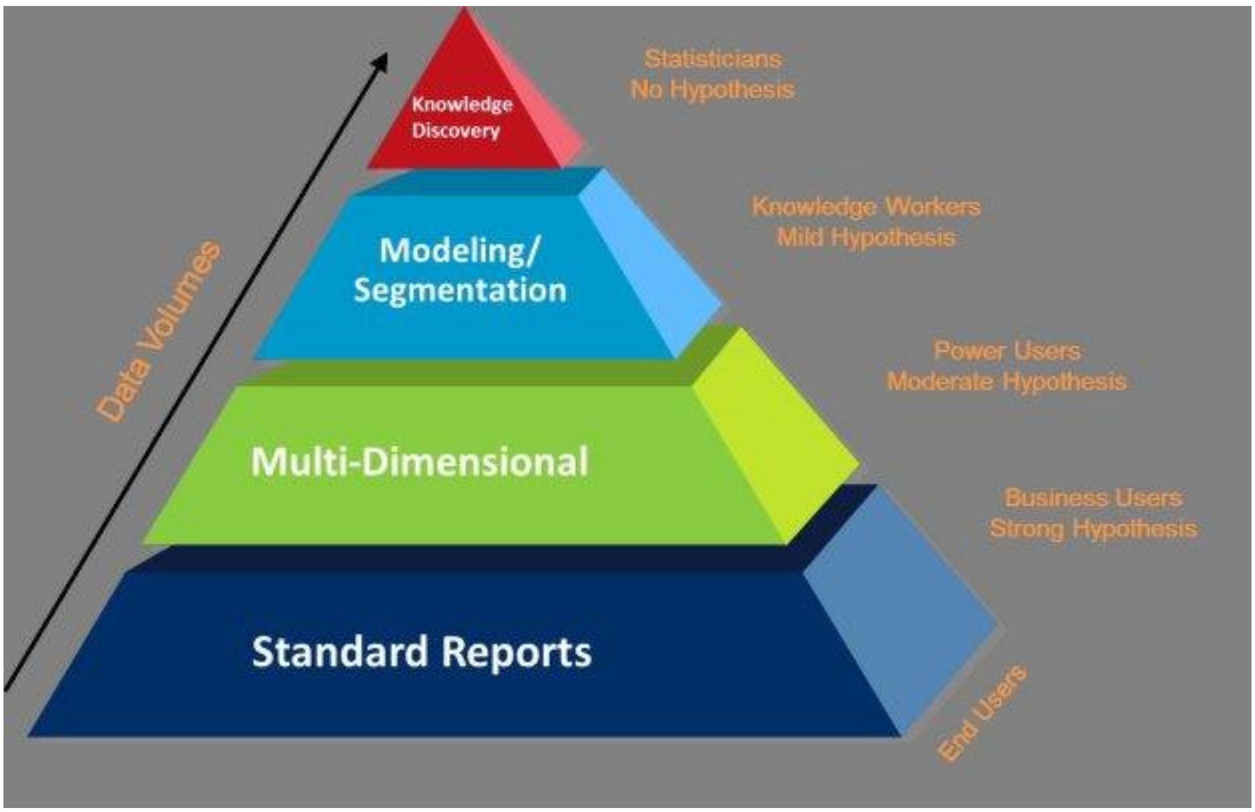
Web of Science (WoS): It is an independent global citation database that connects regional, specialty, data, and patent indexes to the Web of Science Core Collection (Clarivate 2022).

CHAPTER 2 LITERATURE REVIEW

2.1 BUSINESS INTELLIGENCE

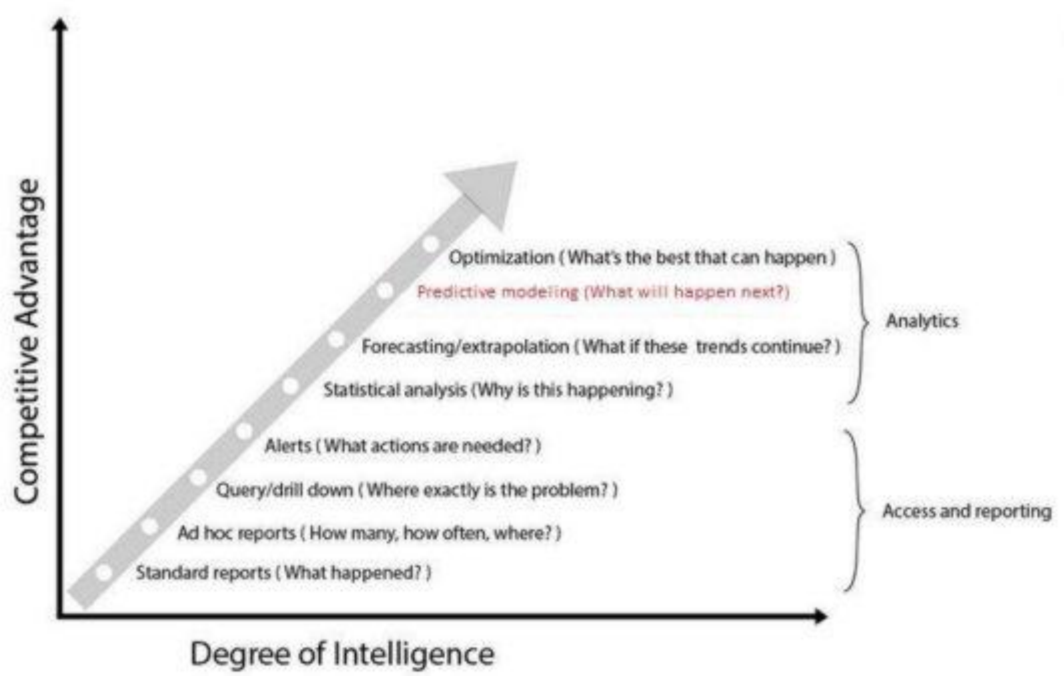
Business Intelligence (BI) and Analytics are computer-supported systems used for identification and to produce new insights and high-quality knowledge to support decision-making (Božič and Dimovski 2019). BI is learning from the business experience which explains the behavioral approach to using informatics and information technology to make decisions. It is an important part of organizational planning to gain intuitive sight and to execute the operations phase by phase based on these informal gatherings (Cao, Duan, and Li 2015). Knowledge workers and data scientists are essential for each company to establish its corporate strategy and planning. The figure below demonstrates knowledge creation is strongly correlated with the skillset of the managers and employees:

FIGURE 2.1: BIG DATA AND DISCOVERY TRIANGLE (DYCHE 2014)



As seen in the figure above, Knowledge Discovery is an input-output process that involves the procedural steps from the creation of the Standard Reports to an evaluation of the scenario analysis. Statisticians create multidimensional models under hypothesis testing. While data-driven decision-making is the extent to which a transforming capability challenges current practice based on data-driven insight, the effectiveness of the business strategy can be specified as responding to change and understanding customers. The environmental ecology of the business is centered around the quality of the products and customer satisfaction. The organization's success factors, process-related success factors, and technology-related success factors are the main determinants of business success analytics; such that these factors determine a clear organizational vision, a well-established business case, well-established project management methodologies, and a scalable technology infrastructure (Parks and Thambusamy 2017). The model below shows how companies can gain a competitive advantage by using analytics:

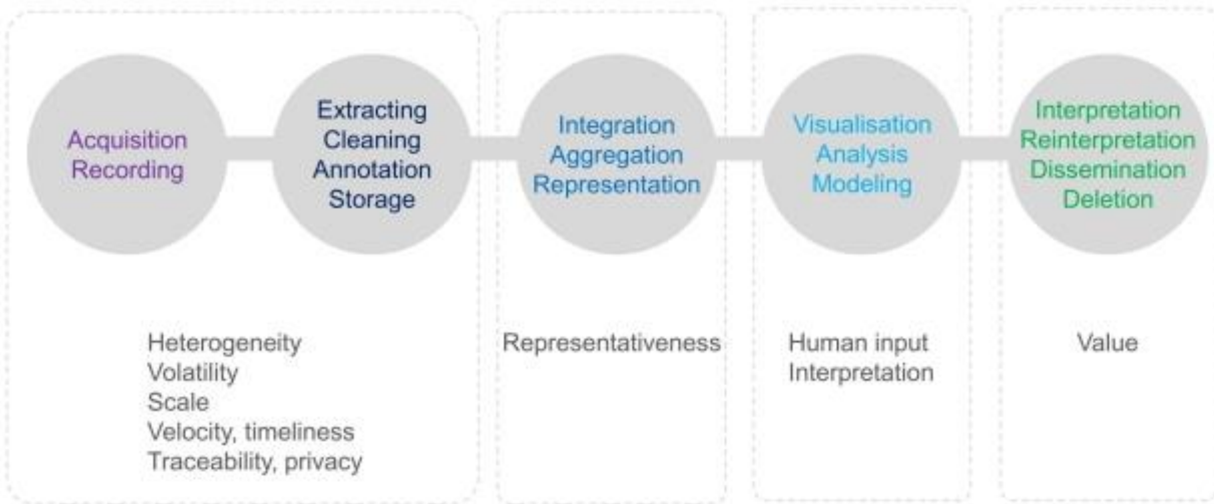
FIGURE 2.2: BUSINESS INTELLIGENCE AND MARKET ADVANTAGE RELATIONAL MODEL (NAJDENOV AND MAKHOUL 2015)



As seen in the figure above, a degree of successful market advantage is increased by using data analytics as a day-to-day operation. Competitive marketing advantage results from using organizational technology sources. BI and Performance Management (PM) systems are based on the visualization and presentation of a large amount of information from several sources about business partners, customers, and internal processes; the emphasis of their functioning is the support decision-making process through retrieval, manipulation, and visualization of data (Cingula 2018). These tools are designated as an information service architecture where each process is consistent with the corporate strategy. Data Analytics is based on the type of industry and organization, as well as the purpose of the use case. A decision management system is a systematic approach to automating and improving operational business decisions toward increasing efficiency (Cingula 2018). Expert-driven planning that relies on expertise, a data-informed decision that relies on the expert to interpret information from the report, a data-guided decision where a predictive analytic model replaces unproven assumptions with information, and a data-driven decision that can be fully automated with running analytic models are the main component of the Data Management System Taxonomy. The taxonomy is a part of the information system architecture of each company.

BI is a sequence of operational processes to provide the right information in the right format and to represent such information to the consumer in real time. Intelligent decision support systems and knowledge management databases are part of these advanced evolutionary stages. The multilayer framework is promoted by casual interdependencies and the holistic design of business analytics. BI Systems' maturity is based on information content quality, information access quality, analytical corporate culture, and the use of information for decision-making (Parks and Thambusamy 2017). At the subunit organizational level, the implications of sophisticated information technologies deal with Bayesian processes with the decentralization capability where multiple operations can be carried out at once. The four stages of automation for BI Systems are information gathering, information analysis, decision making, and action implementation with key performance indicators (Cingula 2018). The model below reflects each step from the information gathering and cleaning to decision-making based on the interpreted data:

FIGURE 2.3: BIG DATA COLLECTION AND ANALYSIS LIFECYCLE (INTERNATIONAL TRANSPORT FORUM 2015)



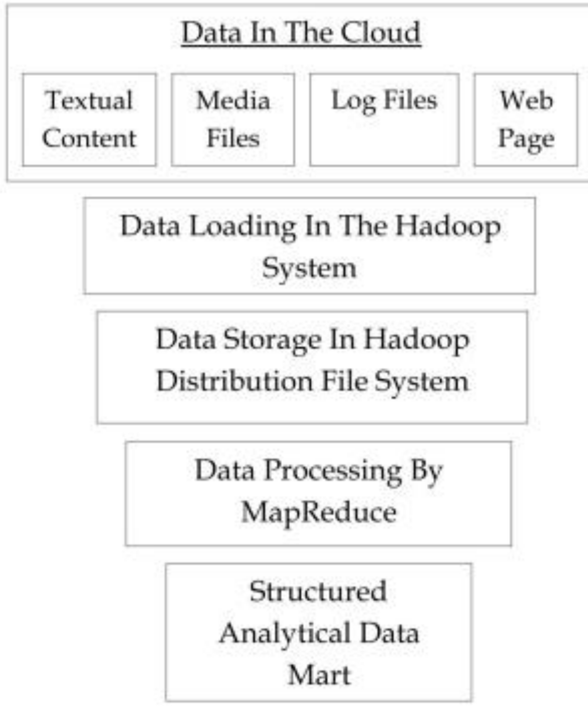
As seen by the model above, input and output processes compute raw datasets from acquisition and extraction to integration and display for desired analysis modeling. Representativeness and visualization are based on information sources and the quality of data. Interpretation of the data is based on the analysis of the model to create a strategic business advantage. While disruptive innovations may result in more productive sectors, sustainable technology enhances corporate operations (Aryal et al. 2020). The convergence of various technologies explores advanced data management and creates opportunities for data analytics, where strategic planning can be implemented with key deliverables. The real-time event, data, and visual discovery accelerate the process for that purpose. A data-centric approach to the development of BI with data analytics can significantly improve marketing analytics to compete with counterpart organizations (Guo et al. 2017). Simon's model for the decision-making process explores the determination of the problem, the selection of alternatives, and the best alternative among them (Najdenov and Makhoul 2015). Each of the three phases goes through the intelligence phase (simplification) where each occasion is analyzed over which a decision should be made, the design phase (validation of model) of developing and evaluating multiple scenarios, and the choice phase (verification and testing) of selecting a particular course of action out of the pool of available courses.

Streamlining analytics would allow firms to control processes during an event to improve outcomes, by paying attention to data flow and reliance on data scientists (Davenport, Barth, and Bean 2012). Categories of organizational sources are governance, culture, people, and technology. Technological, human, and relationship assets may underpin the dynamic capabilities of organizations. Statistics show that the development of big data technology has a direct impact on profitability and productivity and that continuing advancements that are crucial to organizations can increase company activity (Niebel, Rasel, and Viete 2019). The digitization and the collection of real-time data are accelerated with the increasing migration of social media and global economic activities. Retail stores and banks, e-commerce companies, airlines, and tourism industries heavily use these tools to innovate their operations accordingly, where each sector is linked with another on consistent communication. With job complexity and the rate of environmental change, the information processing view organizes to manage uncertainty through deployment (Cao, Duan, and Li 2015). The business perspective includes forecasting uncertainty variables. While automated systems increase access risk both inside and outside of businesses, big data risk is inherited by physical system architecture because of internal control system allowance (Bumblauskas et al. 2017). Data without analysis, knowledge without actionable insights, and ineffective internal communication networks have relative marginal value to the organizations.

The ability to learn, adapt and make decisions based on data collection and quick delivery is improved using analytical tools in business (Akter et al. 2019). Consistent learning and adaptive processes would create an informative culture for the employees and the board of directors. Decentralized firms are better positioned to gain from data analytics since real-time insights are dispersed throughout the business (Rijmenam et al. 2019). The dynamic capabilities that enable the organizations to develop new products and services are micro-foundations of an integrated business model and add to the competitiveness of the firm. The big data strategy facilitates dynamic capabilities to respond to changes in a dynamic environment while sensing, seizing, and transforming information. The use of analytics shifts decision-making to the most knowledgeable people who are the subject matter experts for such technology, which changes the power dynamic. Environmental contingencies that threaten business models are strategic risks, where business continuity depends on the holistic and socio-technical approach. Data analytics can be used to evaluate these risks, known as Black Swan events, where the value creation would be preserved while focusing on evaluating contingencies that threaten the present business model (Rijmenam et al. 2019). For business continuity, creating content is more crucial than maintaining the current framework (Niemimaa et al. 2019). The quality of operations from the gained insights is determined by the effective computation processes. The implementation, which involves a selection of algorithms, statistical learning experiments, and data preparation operations, is what determines the analytical requirements (Nalchigar and Yu 2018). Data preparation and statistical assumptions play an important part in this phenomenon.

One of the most critical aspects of marketing, which can be evaluated with data analytics is brand attachment where the consumer interacts with each trademark. Brand attachment is a crucial aspect in the strength of the connection between consumers and the brand that would provide shopping insights when determining whether to invest in a product (Arya, Sethi, and Paul 2019). Uber and Airbnb are two important brands for consumers as sharing their experiences. There are several ways to use data analytics in marketing to utilize for business purposes. Organizational data sources include transactional data produced by transaction processing systems, unstructured data created by people using social media (e.g., Twitter tweets, and Facebook posts), and sensor data (e.g., GPS data) produced by sensor networks (Hopkins and Hawking 2018). The generation of such data and information is stored in the databases by the data scientists to be utilized for gaining insights. The Decision Engineering System's Decision Service is a functional component that is activated by other processes and events (Cingula 2018). This approach creates less human effort, capital, and time to make services at fewer costs and fewer defects. The sequencing and structure of decisions and the business rules, predictive analytic models, and optimization models are required to develop decision engineering-based models. Decision Engineering activities are decision discovery and modeling, decision service construction and inventory, and analyzing key performance indicators. These distributed information databases create consistent data gathering to support the activities under a standard file system that is called the Knowledge Management System. Hadoop Data Management is a classical Knowledge Management System for storing, processing, structuring, and analyzing shown below:

FIGURE 2.4: DIAGRAM OF HADOOP FRAMEWORK (CHATTOPADHYAY 2016)



As shown in the figure above, different types of data are processed by Hadoop Data Management to create structured analytical data. Knowledge Management System is an operations information architecture that deals with creating, managing, integrating, and maintaining knowledge to support business processes (He, Wang, and Akula 2017). While marketing theory formulates quantitative models intended to approximate stakeholders' behavior and then test those models with data acquired for that purpose, analytics would help with showing alternative ways (Lukosius and Hyman 2018). The virtual dashboards are very effective for simulating necessary tasks, processes, and insights. Visualization based on user experience is a crucial tool for better user services (Bello-Orgaz, Jung, and Camacho 2016). Human-computer interaction is important for visualization software.

The Resource-Based View is an organizational level of capital market theory that suggests firms become more competitive when resources are distributed across the market (Torres, Sidorova, and Jones 2018). While data management involves processes that acquire, store and retrieve information for analyses, data analytics refers to tools and techniques to extract business intelligence. Big Data technologies have significant financial and resource implications, necessitating the development of cutting-edge business solutions that can boost output and enable more informed decision-making (Turner and Atkinson 2018). A firm's absorptive capacity is defined as the ability to recognize and process changing market conditions. The absorptive capacity underlying factors are domain-specific of such industry, firm-specific management, and path-dependent conditions (Božič and Dimovski 2019). Dynamic Capabilities of an organization are an adaptation to changing market conditions as developing new products and services. The main routine operations are opportunistic sensing and seizing and transforming organizations for sustainable growth. Organizational ambidexterity is the ability to respond to changes in the business environment where each firm may encounter environmental ambiguity, which is defined as instances when business relationships are unclear because of a lack of information (Rijmenam et al. 2019). A firm needs to achieve organizational ambidexterity when it faces a competitive environment. This requires companies to recognize new information to adjust dynamic capabilities while focusing on internal and external changes. Dynamic capabilities of the organizations evolve with sensing new opportunities that can influence organizational decision-making. Competitive advantage is derived from a firm's ordinary capabilities that have been transformed through these decision capabilities.

A management perspective on economics makes the resource-based view of the organization an excellent strategy (Krishnamoorthi and Mathew 2018). Cost and time reduction, supporting internal business solutions, and innovating new processes are the main objectives of big data usage in businesses. The platforms that enable high-performance activities are required to execute such actions in the business view. Existing business structure and data scientist talents would play a role in automating new processes. New and hybrid technology environments impact the Return on Investment (ROI) at each company (Davenport and Dyche 2013). The implementation of Data Analytics blends technology and human knowledge. The predictive knowledge and insights will be used to adapt and survive in adverse conditions. Because analytics interaction is built on a triggered series of actions, the sense-response architecture changes as one's familiarity with such information technology increases (Kalaidjieva and Swanson 2002). The level of interaction will become more sophisticated as the complexity increases. The dynamic capabilities that enable organizations to develop new products and services are micro-foundations of an integrated business model and to the competitiveness of the firm (Rijmenam et al. 2019). Predictive analytics is the logical step to establishing a data-driven culture in organizations. Knowledge discovery leverages business actions more than conventional business intelligence, but it may also necessitate business executives to take on larger risks to support discovery operations (Dyche 2014). When business strategies are optimized through the hierarchical stepwise procedure through management, analytics can leverage the managerial processes. This procedure for long-term success takes into account the company's link to its environment as well as consideration of the decision as a unit analysis that covers the key responsibilities of guidance and operational activities of the organization (Harrison 1996). Crisis management handling is more effective when data analytics are used for corporate strategy making.

2.1.1 Black Swan Theory and Heavy-Tailed Risk

Black Swan is a complex theory that which predictive scenarios cannot be predicted based on complex catastrophic events and disruptions (Rijmenam et al. 2019). Understanding customers is the most challenging area to generate insight. The human mind is linked to emotional factors to predict the next behavioral event. The irrational behavior is part of the Black Swan effect that would have an unexpected change in business cycles. The innovative nature is part of the competitive economic theory, where each capital market is expected to be self-sufficient without intervention. Better corporate planning has a positive relationship with the diversification of the company portfolios and with different measures of the sustainability of corporate governance (Verheyden, Eccles, and Feiner 2016). The theory of decision-making determines a series of behavioristic principles based on a decision-maker. A group of choices and individuals' principles define the rational choice theory where decision-makers make choices under certainty with many alternatives. The characteristic of rationality is an indicator of executable actionable knowledge which is called expected utility theory when extreme risks happen with low probabilities. Under ambiguous circumstances, catastrophic damages can be avoided by combining the utility function of a decision-maker with the probability distribution of potential heavy-tailed outcomes (Stankovic and Petrovic 2016). Heavy-tailed distribution can show non-linear risk factors that are involved during daily business operations.

Managing changing stakeholder behaviors is an example of organizational ambidexterity, where dynamic capabilities aid organizations in understanding fluid and unpredictable environments (Rijmenam et al. 2019). Uncertain economic conditions result from the interaction of environmental circumstances of the technological market disruption in a complex context which limits understanding of the consequences of the decision-making due to lack of information. The possibility of undesirable outcomes based on states and actions is necessary for traditional approaches to strategy formulation under uncertainty, but scenario analysis and resilience thinking can increase awareness of such probabilistic conditions (Polasky et al. 2011).

A black swan is an event that can have an unfolding effect on the global economies that organizations' survival capability can be affected due to disruption and uncertainty. The COVID-19 pandemic is a black swan event that affected the economies globally. Data Analytics can be used to observe a dynamic strategic capability in corporate planning during these systemic risks and crises. It can help organizations understand uncertain economic environments to stay competitive while the focus is on day-to-day operations. The business cycles are directly affected by value creation where the agile frameworks play a factor.

Most organizations have crisis management teams, protocols, and business continuity to guide current actions and forecast possible responses to future events including pandemics and unexpected downturn risks. These policies need to reduce business-critical operations and travel, distribute all critical operations across the departments for effective decision-making, diagnose employees at work, or ask them to stay at home if they are sick (Emond and Maese 2020). Although the main emphasis is containing and mitigating the risk from these unexpected events themselves, for the COVID-19 pandemic, companies need to establish a corporate plan for unanticipated business risks and downturns. These actions are updating business intelligence daily necessitating new strategies of mitigation rather than containment, using experts' knowledge and predictive forecasting understanding of what's happening and will happen including epidemic and public health intelligence, and establishing resilience principles in developing policies that also include consistent communication with the employees and evolvability for preparedness for the next possible crisis (Witty and Venecia Liu 2020). These policies for dealing with and resolving the ability to forecast immediate results are get-ready scenarios for current and future situations. Dealing with and resolving the immediate problems that COVID-19 presents to each company's workforce as well as creating resilience protocols that can foresee similar cyclical events will enable businesses to continue operating throughout this pandemic crisis (Craven et al. 2020). Sharing economy platforms need to have consistent operations during a crisis to serve their consumer where predictive analytics can help with gaining insights into which business activity may have stable operations during catastrophic incidents.

The economic hazards are caused by the epidemiological curve's flattening public health control efforts and expectation shocks based on temporary unemployment (Baldwin 2020). Although Markowitz's mean-variance portfolio diversification is used for minimizing the risk factor for financial portfolios, there can be negative diversification effects in heavy-tailed models non-degenerate tail dependence structure meant for going far beyond the classical mean-variance method (Mainik and Embrechts 2013). The uncertainty can affect the investment and management of the firms. The Value-at-Risk (VaR) and the Expected Shortfall (ES) risk management models and frameworks are created for the theory of risk coherent risk measurement (Mainik and Embrechts 2013). VaR is a risk management measure that determines financial losses resulting from a conflicted movement in interest and market rates over a certain holding period (Hitchins 1997). It is a sensitivity limit with an assumption that the rate changes in statistical terms within (+/-)1 standard deviation of the mean. Senior executives of organizations can use this method to gauge the level of uncertainty they are experiencing and make decisions based on the total institution's aggregate risk estimate. This is an important model to observe the financial health of each company with its risk management activities under Black Swan events like disease pandemics because the cost-benefit curve is affected due to the financial constraints of the companies. The analytical toolset can be used to predict such outcomes before they happen and take measurements with risk models to be ready. VaR is designed to work within a stable environment for a well-defined single and multi-factor portfolio to achieve some insights into the sensitivities of the portfolio and to observe the limitations based on the further tails of the distribution (Pratt 2010). This is crucial for sharing economy as Uber and Airbnb can continue to serve their operations and avoid default. The requirement for safety measures to prevent a potential default was hastened by COVID-19. Some of the biggest systemic shocks to the sharing economy's financial stability can be avoided using risk models.

2.2 BUSINESS ANALYTICS

The historical contexts of big data began with Frederick Winslow Taylor and the scientific management techniques which represented the analyses of work-related data (Bumblauskas et al. 2017). When the exponential growth of data has resulted from the instantaneous sharing capability of the Internet and social media, business analytics emphasized the need for specific analytical skills in terms of training and educational purposes. The table below describes some of the usages how information is utilized from the technological and analytical perspectives:

TABLE 2.1: ROLE OF BIG DATA IN MAKING DECISIONS (JEBLE, KUMARI, AND PATIL 2018)

Big Data Source	References	Big Data-Driven Insights	Actionable Decisions
Google Search for a product or brand		-Customer intention to buy a product -Identify customer preference for a brand	-Predicting demand for the product

Google Search by specific keywords	Mayer-Schonberger and Cukier, 2013	-What information citizens are looking for or concerned about	-Predict the spread of flu by geography by regions
Amazon Search	Amazon.com website	-Customer intention to buy a product	-Reminder to the customer that next time she/he visits the site leading to chances of a sale
Amazon Purchase history	Amazon.com website	-Using association rules mined from billions of records, identify which different products are bought by customers	-Product recommendation (customer who bought, also bought this)
Walmart POS data	Waller and Fawcett, 2013 Dyche, 2014	-Using association rules mined from billions of records, identify which products customers buy together (market basket analysis) -Facing disasters such as hurricanes, people buy some unusual things in addition to the usual water, batteries, etc.	-Store layout redesign to place such products together -Inventory planning based on buying patterns before disasters such as hurricanes

Data from telematics sensors Role of Big Data in Making Decisions used by UPS vehicles	Davenport and Dyche, 2013	-Information about speed, routes, direction, braking, drive train performance	-Redesign Routes lead to saving of millions of gallons of fuel
Call center logs, online usage of accounts	Davenport and Dyche, 2013	-Create a complete profile for the customer journey	-Design future strategies for improved customer service

The facts and insights are very helpful in determining each company's marketing edge and financial performance, as seen in the table above. Business analytics is the creation and utilization of information and intelligence to strategize corporate planning based on data to support an organization's financial goals (Parks and Thambusamy 2017). That includes decision management, content analytics, planning and forecasting, discovery and exploration, business intelligence, predictive analytics, data and content management, information integration, and governance. With the help of analytics, which is based on the extensive use of data, statistical, and quantitative analysis through explanatory-predictive models and fact-based management to drive decisions, economies are developing their competitive strategies around data-driven insights that are computing positive results (Davenport and Harris 2010). International companies can have a substantial advantage with the usage of predictive models from their counterparts. Through the intervention of a data-driven environment, business analytics has a notable impact on data-driven decision-making (Cao, Duan, and Li 2015). Benefit and costs analysis is described in the table below:

TABLE 2.2: COST-BENEFIT ANALYSIS OF BDA (BARTOSIK-PURGAT AND RATAJZAK-MROZEK 2018)

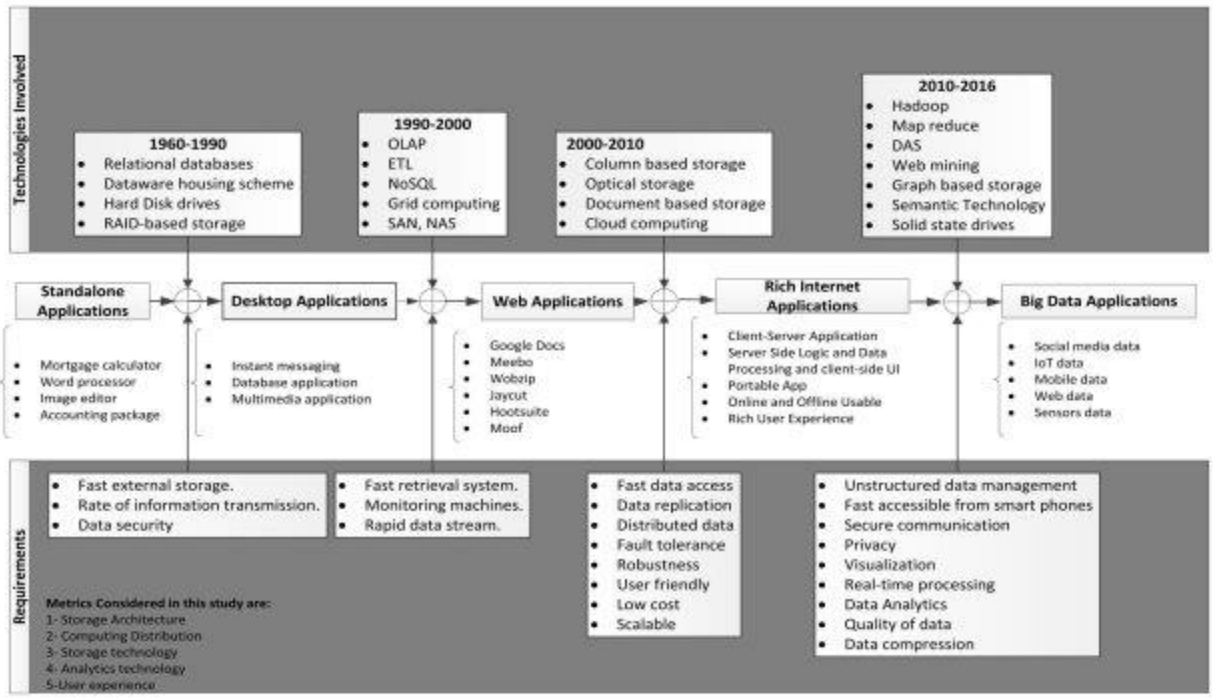
Benefit-Cost Analysis	**Benefits**	**Costs**
For Customers and Individual Users	-getting a personalized offer if they use different sources -saving time when searching for products or information about them	-too much surveillance on individual users' Internet activity
For Companies	-provision of information about the market (both individual consumers and institutional units) -time and cost reduction -more probability of sales increase -more probability of getting new customers. -better financial results	-complexity of data which comes from many different sources (there is a need for their adaptation, segregation, and conversion into different information systems) -the necessity for strong control over the data because of its complexity and variability

		-data storage -data analysis (necessity to use advanced analysis tools and systems)

Even though it is expensive to produce and labor-intensive to utilize, data analytics is required to have a clear competitive advantage in company planning, as demonstrated in the table above. Information systems platform that supports office operations, a customer experience platform, a data and analytics platform with information management, an Internet of things platform that monitors and connects physical assets, an ecosystem platform that connects external ecosystems, and an integration platform that supports the integration of all above platforms are main business platforms (Yablonsky 2018). Input-Process-Output Model for Information Systems, where the interaction can be evaluated by comparing the input with the expected output from the microeconomic perspective. The architecture of computing systems is unique to the nature of each company for its operations, while each process needs to synchronize by the data scientists for consistent services. A data scientist uses analytical tools for innovating ways to gain value through the Big Data Value chain (Yablonsky 2018). The innovations rely on the data scientists' and engineers' knowledge and talent. The computation of actionable knowledge from big data depends on valid and timely information, the ability to make informed choices, and monitoring both the validity of input information and the implementation of the decisions (Bumblauskas et al. 2017). The shift toward analytics-supported performance indicators enables decision-makers to utilize additional data in consideration of different courses of action when pursuing a set of goals. The forecast and outcome are positioned better when the resource-based approach is used which helps lower logistics costs and better organization of the labor force (Popovič et al. 2018).

Optimizing core business activities, selling data services, and creating new innovative models are the main factors of these systems. Aspirational, experienced, and transformed are the main analytics capabilities of organizations that identify business success factors and reduce costs while guiding a centralized analytics unit (LaValle et al. 2011). The promotion of success is based on talented data scientists and engineers. An ideal business analytics software includes predictive analytics and data mining, data visualization, forecasting, model management, operations research, and quality improvement (Ittmann 2015). Each part is incorporated into the software architecture of the company. The analytics dashboard represents organizations' routine operations, discrepancies in processes, and insights from the statistical models (Banerjee, Bandyopadhyay, and Acharya 2013). These processes can also reflect the progress view of the daily business operations. The information architecture of companies can be shown as the model below to make a better sense of how the data is processed and visualized under such a scenario:

FIGURE 2.5: GENESIS OF BIG DATA APPLICATIONS AND THE DEVELOPMENT OF THE ARCHITECTURE (YAQOOB ET AL. 2016)

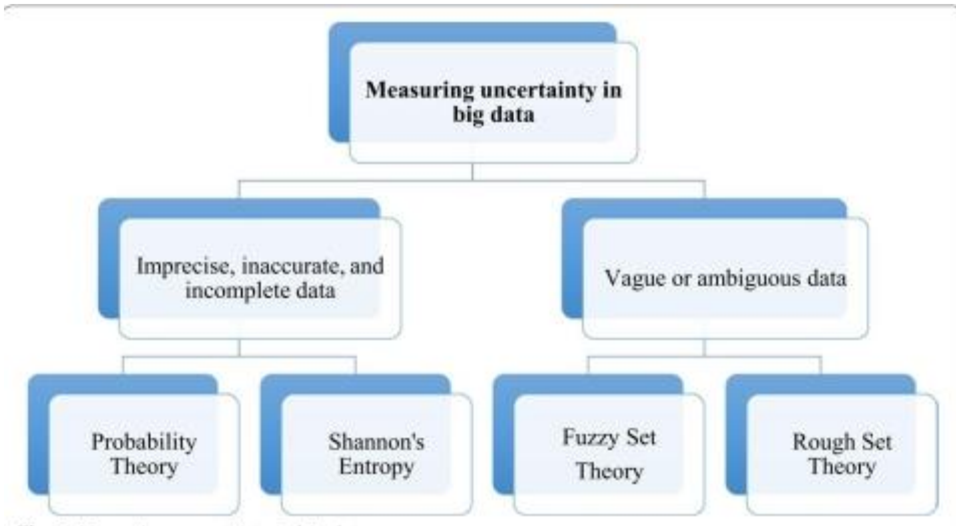


Each company's information systems design incorporates a big data architecture that will be employed in their operations, as illustrated in the table above. Uber and Airbnb have similar types of data architecture for consumers and partners. Their mobile app is connected to the stand-alone data architecture to execute the operations and store the data.

Processing information is a set of analytical and functional tools to gain insights into business processes and uncover hidden patterns from the business intelligence view. Data Analytics is the computation of data, obtained from different sources, via statistical and quantitative analysis, explanatory and predictive models, and fact-based management to guide the decision-making and activities of the stakeholders (Davenport and Harris 2007). Extraction, loading, and transformation of the information are the main processes. It is mostly applied in E-commerce by creating business value and improving business value by generating insights and focusing on the discovery of new consumer products (Akter and Wamba 2016). Retail stores use this feedback process to improve their sales and better service operations. Social media and crowdsourcing systems companies innovated web intelligence and analytics to enable identifying opportunities (Bumblauskas et al. 2017). Main data methodologies are briefly regression analyses that reflect relations among two variables, social network analyses that establish a relationship among the individuals and organizations, machine learning where natural language processing is enabled to analyze human speech, and a genetic algorithm that represents complex human tasks, association rule learning to find interesting relationships between variables hidden among large datasets, and sentiment analysis which focuses on feelings that have no meaning (Chattopadhyay 2016). They are part of the service enterprise platform of each company.

Data analytics is a combination of data analysis and mining of the historical relationship of information and visualization of such information (Sun, Strang, and Firmin 2017). Businesses use data analytics to improve their sales and operations. Using the scientific method to turn data into insights for optimal decision-making, lets managers understand the complexities of company procedures and control risks, allowing businesses to make decisions faster and with more knowledge (Vidgen, Shaw, and Grant 2017). Data Mining employs advanced statistical methods to analyze data available through Data Warehouse, to identify the possible relationship, patterns, and anomalies for rational decision making. The ambiguity and unnecessary relations between structures are removed based on the statistical analysis. This can be shown below:

FIGURE 2.6: MEASURING UNCERTAINTY IN BIG DATA (HARIRI, FREDERICKS, AND BOWERS 2019)



The figure above demonstrates how raw data is collected and processed using various statistical techniques to ascertain the degree of uncertainty. To compute, each data structure is categorized as either incomplete or ambiguous. The collection, interpretation, and synthesis of data in the context of organizational decision-making are the functions of an organization's information processing capabilities (Cao, Duan, and Li 2015). Synthesis of the data is an important part of the process to understand what it means. The important components of advanced business analytics are the business view which represents an enterprise in terms of strategies, decisions, and required insights; the analytics design view which represents the core design of the analytical system; the data preparation view which represents data preparation processes; and design set of design catalogs that codifies, organize, and express analytics design knowledge and expertise in terms of conceptual models (Nalchigar and Yu 2018). Hadoop Distributed File System (HDFS) to store very large datasets and MapReduce algorithm to solve the web search index creation problem are two main components of the Hadoop big data framework (Emani, Cullot, and Nicolle 2015). Hadoop can transform, extract, and load big data sets.

Organizations that are data-driven have higher operating performance, higher customer satisfaction, and optimal profit-to-revenue ratios. This is done by empowering them to make customer-centric marketing choices that will assist them in addressing key factors that will help them enhance service. The data analytics competency covers data governance over its lifecycle, data analytics to transform data to meet business goals, and data visualization to reflect data in multiple visual ways to highlight patterns and trends to aid corporate decision-making (Monterio 2019). Product innovation and workforce planning both provide key success indicators. By using data analytics as an enterprise-wide solution, businesses can improve their ability to calculate, assess, and manage risk. Organizations may use data analytics to increase profitability and risk prevention by using variables such as the use of people, processes, frequency of time, and rate of success (Taylor et al. 2017). Business managers must define risks and rewards when managing and modifying current business models and incorporating analytics into their operations. Data-driven planning based on analytics is an integral part of crisis management, where each decision is critical to the survival of each organization. This functionality is extremely beneficial to sharing economy services in terms of optimizing their business planning. Since the start of COVID-19, Uber and Airbnb have made significant commitments to their operations based on key performance metrics.

As noted in the introduction, there are three different kinds of data analytics with different purposes, and each stage increases in complexity. Descriptive analytics is a form of analytics that defines events over time. Predictive analytics focuses on the cause of any occurrence by making hypotheses based on a variety of datasets. Prescriptive analytics denotes a technique for intervention.

Descriptive analytics uses methods and statistics to explain and identify a problem's current state (what happened? or what is happening?). In unpredictable times, descriptive analytics allows businesses to better sense opportunities (Akter et al. 2019). It lays the groundwork for converting data into facts – a look back at what happened. Offering input into what has happened in their internal and external environments, helps companies to understand, filter, form, and calibrate opportunities. Responding to the changing environment improves the organization's internal processes. During COVID-19, this is a crucial aspect to consider when analyzing current events and situations.

Organizations can take advantage of opportunities by transforming processes and improving strategy building with predictive analytics (Jeble, Kumari, and Patil 2018). This collection of tools is used to create business practices and dynamic reports, as well as to provide insight into a particular issue. It describes a phenomenon that has occurred in the past. It offers advanced predictions as well as the ability to model future results and outcomes – the ability to gain insight into current processing. Forecasting what will happen, improves risk prevention in the company. Using historical data to predict future patterns. Predictive approaches can be used to assess the issues and difficulties with the sharing economy during COVID-19, and decisions can be taken based on possible scenario analyses.

Prescriptive analytics is a branch of data analytics that focuses on determining the best course of action in each situation based on the data available (Rijmenam et al. 2019). This process includes the items that are known about the data, the decision itself, and the expected outcome of the decision. It interprets data and recommends actions using machine learning techniques and dynamic rule engines – the foresight view of what to expect and what to do next for an actionable suggestion about how to proceed (Hair 2007). Data processing techniques and algorithms, along with analytics forecasting and modeling capabilities, are used to increase business performance. Suggested best-case and worst-case scenarios can be tested during COVID-19 to construct a secure and productive work atmosphere. Prescriptive analytics is the next step in the planning process, and it is the most developed of the three. Each cooperative strategy and forecast outcome based on market scenarios visualized using a hybrid model of data analytics improves the level of knowledge sharing (Ghasemaghaei 2019). It is a vital part of the effective and stable operations for crisis management during COVID-19 to disseminate information and acquired knowledge.

The application of business analytics in a data-driven environment demonstrates that there is a way to improve management competence by providing insightful data (Cao, Duan, and Li 2015). These observations will pave the way for a good business strategy that puts them ahead of the competition. Because of advancements in information technology, data analytics has enabled service technology systems to create innovative ways to respond to customer needs. Since sharing economy providers must invest in technology infrastructure to work, a data analytics approach to crisis management allows for dynamic capabilities to adapt to changes. Descriptive analytics for problem diagnosis and predictive analytics for forecasting are the main areas of business analytics activity (Larose and Larose, 2015). This research aims to adopt a predictive data analytic approach to examining the role of data analytics for crisis management in the cases of Uber and Airbnb.

2.2.1 Predictive Analytics

Predictive analytics examines a vast quantity of data using several variables to predict the likely outcome of an event or the possibility that a condition will occur (Sharma and Dadhich 2014). The methods can include clustering, decision trees, market basket analysis, regression modeling, neural nets, genetic algorithms, and text mining. The predictor is the core element, as a variable that can be measured for an individual or an entity to predict future behavior. The table below shows how explanatory and predictive modeling techniques are employed and analyzed:

TABLE 2.3: EXPLANATORY STATISTICAL MODELLING AND PREDICTIVE ANALYTICS (NAJDENOV AND MAKHOUL 2015)

Step	**Explanatory**	**Predictive**
Analysis Goal	Explanatory statistical models are used for testing causal hypotheses.	Predictive models are used for predicting new observations and assessing predictability levels.
Variables of Interest	Operationalized variables are used only as instruments to study the underlying conceptual constructs and the relationship between them.	The observed, measurable variables are the focus.
Model Building Optimized Function	In explanatory modeling, the focus is on minimizing bias. The main risks are Type 1 and Type 2 errors.	In predictive modeling, the focus is on minimizing the combined bias and variance. The main risk is over-fitting.

Model Building Constraints	The empirical model must be interpretable, must support statistical testing of the hypotheses interest, and must adhere to the theoretical model (e.g., in terms of form, variables, and specification).	Must use variables that are available at the time of model deployment.
Model Evaluation	Explanatory power is measured by strength-of-fit measures and tests (e.g., R2 and statistical significance of coefficients).	Predictive power is measured by the accuracy of out-of-sample predictions.

As seen in the table above, although predictive models can be used as a forecasting tool based on statistical approaches applied to the same dataset, explanatory models are used for diagnosis and observation based on previous data. Building a predictive analytic model requires access to historical data from different sources, their understanding of methodology, preparation, and application of different statistical predictive techniques, and building, testing, and deploying machine learning and data mining methods. It is a combination of software components designed to enable the analysis of a set of data sources to determine the mathematical relationships within the data and to produce a model that manifested those relationships. A predictive analytics system can support different data mining techniques like rule induction, decision trees, linear regression, clustering, K-means, and nearest neighbor. The difference between explaining the differences and predicting is based on the analysis goal, variables of interest, model-building optimized function, model-building constraints, and model evaluation. Predicting is an act of using information gathering to develop alternatives for a problem. Management of the organization executes decision prediction models with strategic planning and operational control procedures.

Predictive Analytics is a component of business intelligence that is used for making predictions of future behaviors and outcomes, through mathematical and statistical methods (Halladay 2013). It can be utilized in different business sectors based on its purpose. These are briefly (Sharma and Dadhich 2014): (a) Analytical Financial Service that shows the indicators for time and revenue analysis; (b) Analytical retailing and customer relationship management that provides the indicators for customized shopping experiences; (c) Analytical clinical decision support systems to determine which patients are at risk of developing certain disease; (d) Analytical manufacturing support systems to reflects maximum benefits with consumption of minimum resources; (e) Analytical study of collection that represents a set of delinquent customers who do not make their payments on time; (f) Analytical customer retention that emphasizes the indicators of efforts on maintaining continuous business services; (g) Analytical marketing that analyzes customer behavior. With the incorporation of predictive analytics into the technical structure, the technical competency of decision-making processes can be improved.

The business view allows organizations to see new constructs of business relationships, interpret the moment details of a business, and to gaining insights into the future. There are different types of Predictive Analytics. These are as follows (Sharma and Dadhich 2014): (a) Predictive Modeling as mathematically representing underlying relationships in historical data to describe the data; (b) Descriptive Model to quantify relationships in data to classify customers and prospects; (c) Inferential Model to reflect the level of significance for determining with what validity data can be said to indicate some conclusions.

Predictive Modeling and analytics with their business processes need to be aligned correctly to increase the organizations' business value, such as Amazon and eBay. Data mining and predictive analytics are used by companies by determining relationships visualized on graphical user interfaces, such as sales performance by geographical area in data through hypotheses testing and, model building and validation (Hair 2007). They can observe the changes in their business distribution as well as business operations. Demand Signal Analytics is the next-level technology in business forecasting which uses a combination of visual analytics and predictive analytics to observe changes in demand with minimum latency (Chase 2014). The perceived level of competence helps turn descriptive metrics into insights by using models to predict the future. The maturity model is a road map for realizing the strategic benefits that investment in predictive analytics can offer. Marketers use predictive analytics to understand consumer choices to establish personalized data-driven management strategies. Amazon’s recommendation system for products, Walmart’s real-time instantaneous merchandise shelving, and Google’s website analytical tools are examples of these systems. Each product can be an avatar as a domain in the scenario world for evaluating the variables affecting the shopping trends. Customer value measurement increases with the integration of marketing tools to analyze a significant number of datasets. Complexity increases with the integration of marketing tools. Although predictive knowledge is helpful for business operations, it does not necessarily reflect consumer intent when the interaction is the key (One Team Creative Services 2015). The main purpose is to find and visualize possible scenarios and take the necessary steps for market fluctuations.

Businesses use predictive analytics due to high return investment advantages (Margulis 2016). They employ different mathematical and statistical techniques to accomplish forecasting modeling tasks. The predictive analytics maturity map determines the skill competency for effective implementation and usage of such tools, where organizations maintain small teams. Highly competent organizations would have increased sales due to the development of consumers' insights, as each company reflects each operation in real-time. Predictive analysis has become crucial since COVID-19 started.

2.3 SHARING ECONOMY

Sharing economy is transitory access to goods and services as opposed to long-term ownership (Bardhi and Eckhardt 2012; Kumar, Lahiri, and Dogan 2018). It is one of the most innovative ideas that will change the world. It is founded on mutual trust between the institutionalized trust of an entrepreneur starting a company to provide operations and to trust consumers (Stemler 2016). Mutual trust is based on customer and employee ratings. Three pillars of the foundational cores of the sharing economy are accessibility, platform, and community (Acquire, Daudigeos, and Pinkse 2017). Job creation by utilizing capacity, increasing environmental sustainability by enabling sharing of products and services locally, and diversified products and services variety, consumer safety, and microbusiness protections of participating shared economy are the main benefits.

The exchange between buyers and sellers has been facilitated by the digital revolution (Eckhardt et al. 2019). As a result of technological advancement, societies have evolved. A rising pattern of consumption behavior along with the digital mobile technologies enabled accessing and reusing the products to utilize the idle capacity, where the traditional business model has begun transforming to adapt (Kathan, Matzler, and Veider 2016; Cockayne 2016; Belk 2014).

The market mediation is established through the service platform that can be installed on mobile and other technological ecosystems, including smartphones, tablets, and desktops. Part-time employment distinguishes the thin line between full employment and market mediation, which is based on market-based processes (Sundararajan 2016a). Customer shopping behavior is changed consistently by easier access to such platforms. Consumers have temporary access to underutilized physical assets through an intermediating service platform that organizes exchange operations among economic actors (Frenken and Schor 2017; Perren and Kozinets 2018). That alters our way of life in a disruptive way.

P2P access in the sharing economy gives limited access to underutilized assets and services (Stanoevska-Slabeva, Lenz-Kesekamp, and Suter 2017). Sharing marketplace services collect all types of information while fulfilling their services. Carriers of information can be impersonal (online sources, physical documents, etc.) or interpersonal (friends, colleagues, etc.) on a variety of online or offline channels (Wang, Sarkar, and Shah 2017). The cost-benefit perspective is based on quality and affordability. Personal behavioral changes may modify the service offerings. The mutual dependence on smartphone technology and social media groups are the main elemental factors of sharing economy (Gloss et al. 2016). This dependence determines the survivability of these companies.

Sharing platforms utilize two-sided market settings (demand and supply) through an asymmetrical interaction and the design of prices and subsidies (Fang, Huang, and Wierman 2017). Maximizing revenue and social welfare is the goal of the shared economy such that maximizing demand is enabled by the affordable pricing strategy. Policies are required to lay the foundation for embracing greater transparency, establishing service standards for each type of service, enhancing feedback mechanisms to provide guidelines, and viewing privacy as a chance to diversify the services that could be provided as well as to safeguard the privacy policies of consumer and service platforms (Ranzini et al. 2018). Transparency and ratings are part of the evolutionary process for better services. There are four principles of collaborative consumption for sharing economy to operate (Dillahunt and Malone 2015):

i. Trust between strangers: Sharing your home requires some level of trust that the consumer, in this case, the tenant, will not destroy.

ii. Idling capacity: The unused potential of resources, such as the empty seats when you drive a vehicle alone, is known as idling capacity.

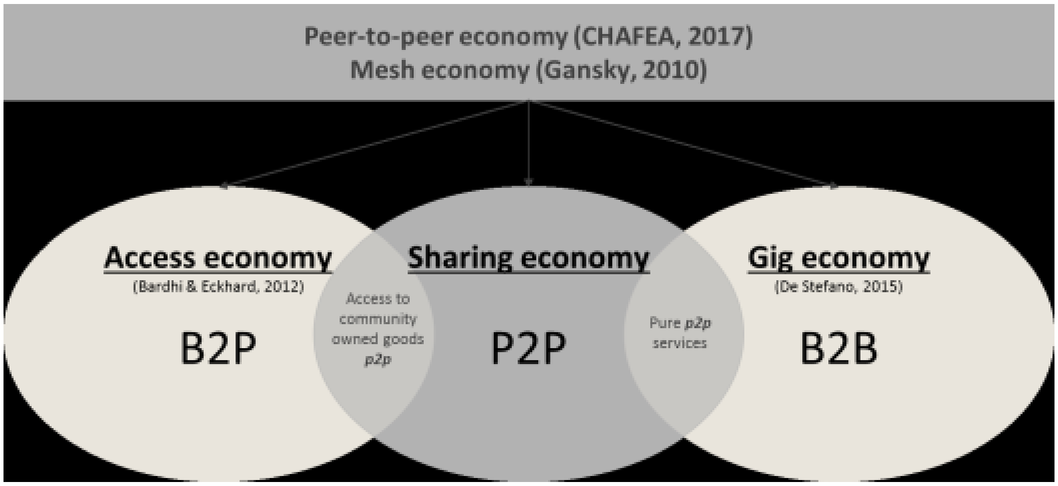
iii. Critical mass: It ensures that customers within the sharing economy feel that enough choices exist for them to feel satisfied (social proof).

iv. Belief in commons: Participating in these platforms, both by sharing and consuming, supports the system and adds value to the community.

2.3.1 Service Enterprise Platforms (SEPs)

According to the European Commission, the sharing economy involves categories of actors (Stanoevska-Slabeva, Lenz-Kesekamp, and Suter 2017). These are providers, consumers, and Service Enterprise Platforms (SEPs). A peer provider is a professional company provider that offers services asynchronously for a profit-seeking motive. SEPs are digital platforms that act as intermediaries while governance policy capabilities are part of the enterprise, where the added value is the platform's involvement in the sharing transaction. The model below clearly shows how the sharing economy is a part of the access economy and gig economy:

FIGURE 2.7: OVERVIEW OF SHARING ECONOMY TERMS AND RELATIONSHIP (STANOEVSKA-SLABEVA ET AL. 2017)



Peer-to-peer (P2P) services to assist with corporate operations, as well as community-owned assets with idle capacity, can be advantageous to the sharing economy, as illustrated in the table. It is part of the consumer economy that consumers and employees can take advantage of by accessing community-owned goods through P2P services. The layers of the electronic catalog of SEPs are the following categories (Stanoevska-Slabeva, Lenz-Kesekamp, and Suter 2017):

i. Peer providers and goods and services offered: Peer providers are private persons offering their private goods and services over the platform to other peers.

ii. Peer consumers: They are users that consume goods and services offered by a peer provide.

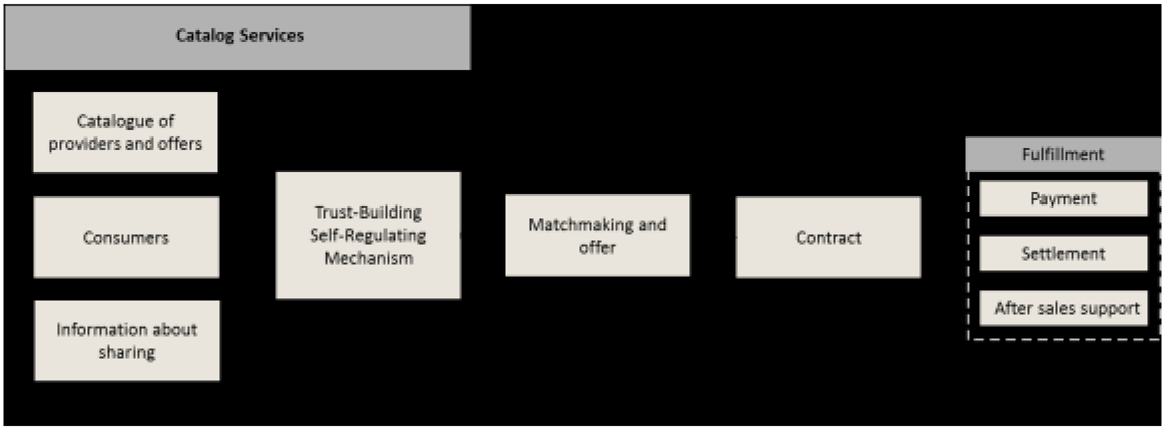
iii. Information about sharing: Peers active on SEPs are private persons that have no experience in presenting and setting prices for their goods and services.

iv. Trust-building and self-regulating mechanisms: Sharing transactions impose specific requirements on the electronic catalog functionality of SEPs. The main components of trust and self-regulation mechanisms are:

   a. Binding terms and conditions of participating on the platform provide a common ground for sharing transactions and participation in SEPs.
   b. Provider and consumer ratings are exclusive information provided by SEP and are critical to its success.
   c. Verification of peers' data and information for the trust-building function of SEPs.
   d. A background check of offered private property that is shared on the platform.
   e. Control of illegal content.
   f. Functionality to exclude users from the platform and share transactions.

These service platforms act as an intermediary for arranging services and transactional activities, including trust-building phenomena. The model below reflects sharing and matchmaking procedurally from receiving the request from the consumer to executing the sales:

FIGURE 2.8: OVERVIEW OF THE COMPONENTS OF A MARKET TRANSACTION ON SEPS RELATIONSHIP (STANOEVSKA-SLABEVA, LENZ-KESEKAMP, AND SUTER 2017)



Matchmaking as illustrated in the model, which is based on ratings between the consumer and the employee who provides the service, is used to gather the necessary information. The contract is the agreement for temporary access to services for consumers as well as for these companies. The design aspect that defines the culture of a SEP Relationship (Stanoevska-Slabeva, Lenz-Kesekamp, and Suter 2017):

i. Peer friendliness for a supportive and hierarchical environment.

ii. Regulation friendliness for establishing a dialogue with the regulatory authorities.

iii. Cooperation in the relationship with other platforms for participating functionalities (navigation, lobbying activities, etc.).

2.3.2 Overview of Categories of SEPs

The base of the corporate sharing platforms on business-to-business (B2B) platforms is designed to outreach the consumer without an agent. The categories are shown in the table:

Table 2.4: Overview of Categories of SEPs (Stanoevska-Slabeva, Lenz-Kesekamp, and Suter 2017)

Category	Description
Food	SEPs that offer food sharing in different forms
Goods	Includes SEPs renting or borrowing all kinds of objects, usually consumer goods such as books, clothes, garden tools
Learning	SEPs enable students or teachers to share learning materials as well as online instructions led by peers
Logistics	SEPs support crowdsourced delivery services by enabling last-mile delivery
Money	SEPs facilitate the crowdfunding of consumer loans, business loans, or equity
Services	Includes a varied range of on-demand services for household chores, design, or computer programming work, and administrative tasks
Space	Refers to SEPs intermediating sharing of space, e.g., storage and office space, vacation rentals, and even gardening tools
Transportation	SEP supports car-sharing and ride-hailing services built to transport people

Each SEP is created for a certain business type that offers services that are optimized based on a customer-centric approach, as shown in the table. Each categorization domain focuses on a certain activity to better serve its clients and meet their needs.

2.3.3 Home Sharing Services and Airbnb

In a mobile and networked society, network sociality is the medium where the interaction between hospitality and technology takes place (Ikkala and Lampinen 2015). The existence of a clear price may provide better services through interpersonal connections. P2P businesses are facilitated by marketplaces with the interim purpose of matching suppliers willing to share underutilized commodities or services with consumers who require them (Ke 2017). Room sharing is a new fashionable activity that offers convenience in the hospitality and tourism industry. Home sharing is the interaction and the exchange of accommodation that occurs via hospitality-exchange services (Ikkala and Lampinen 2015). The interaction between the host and guests is in the form of sociability where hospitality is part of this transactional space. This interaction includes offering accommodation, food, and expressions of gratitude. The fundamental idea behind Airbnb, which was initially called Airbed & Breakfast and began as an Internet firm in August 2008, is to rent out free space in one's flat or house (Aydin 2019). This is an innovation while each homeowner can utilize unused rooms. It is a home-sharing exchange service in which homeowners can rent parts of their houses for a short term as the nature of the social exchange (Ikkala & Lampinen, 2014). In this approach, homeowners can earn some extra money from their unoccupied accommodation, while tourists can benefit at a reasonable cost. The founders of Airbnb established a technology platform that introduces a new business model that would challenge the traditional hotel business (Kavadias, Ladas, and Loch 2016). Its philosophy is based on the regulated lower prices due to not owning or managing physical assets, with a more personal and diversified service. The online platform matches travelers who looking for accommodation with homeowners willing to share a room or house, where Airbnb takes a percentage of the rent. It is a community marketplace for people to list and book accommodations around the world (Stemler 2016). Hospitality is a sort of sociability that takes place in this transactional area between the host and the guest. To foster safety and trust, it offers user evaluations and a verified ID process. This relationship also involves providing lodging, food, and displays of thanks. There are three identifiable domains of sociability. These are respectively (Ikkala and Lampinen 2015):

i. The social domain: The social settings in which hospitality takes place, along with the social functions.

ii. The private domain: It incorporates how hospitality is acted out in domestic settings.

iii. The commercial domain: The domain of economic activity.

The expansion of the sharing economy benefits cities and municipalities by improving resource allocation (Quattrone et al. 2016). Through its matching network, which connects homeowners and renters, Airbnb bases its listings on the renting of a single room or an entire apartment. The features of demand may alter due to economic dynamics and local government initiatives. Airbnb had 140 thousand guest arrivals in 2010 and an estimated 164 million travelers in 2018 (Guttentag 2019). Raising the price of the property and a devalued price of renting are common behaviors in these ongoing negotiations. It has now more than two million listings located in more than 191 countries and has accumulated more than 60 million guests (Ke, 2017). Accommodation was one of the most important factors during the pandemic, with stay-at-home orders and remote-work procedures. Airbnb is a great crisis management case study where data analytics is used during the pandemic for safe services and risk prevention.

2.3.4 Ride-Hailing Platforms and Uber

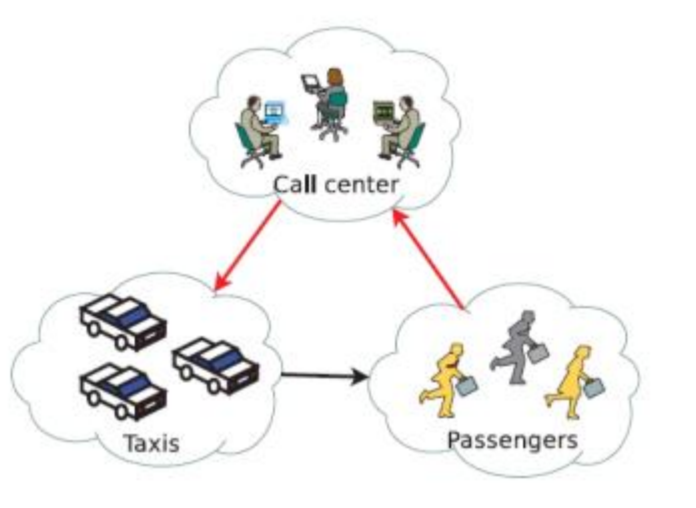
Car rental and ride-sharing sectors benefit from trust-based commercial sharing where they create employment for drivers and benefits for users (Kashyap and Bhatia 2018; Kobis, Soraperra, and Shalvi 2021). The goal of ride-hailing services is to make transportation more affordable and convenient for customers. Maximization of the driver earnings and the optimization of the demand through a shared ride setting for economic pricing are two outcomes of the ride-hailing platforms (Chaudhari, Byers, and Terzi 2018). This is enabled by mobile technologies and service providers. The surge multiplier-based surge pricing includes a minimum base fare, a cost per mile, a cost per minute, as well as extra fees (Chen, Mislove, and Wilson 2015). The mobile shows the closest available cars within that area for the convenience a driver assigns for the requested ride. Ridesharing has the potential of addressing socioeconomic factors related to transportation by improving the efficiency of passenger-to-driver assignments (Asghari and Shahabi 2017). Due to ride-hailing services, employment levels may increase, which would assist the economy in growth.

2.3.4.1 UBER BUSINESS MODEL

Car-sharing services divide into P2P car rental and taxi services (Stemler 2016). For scheduling the drivers and planning the journeys, traditional taxi firms typically use a dispatch service. As an online marketplace for drivers and riders, Uber was established in 2009 (Kooti et al. 2017). It started as an app platform for allowing users to request a car to pick them up. Ride requests are assigned to Uber drivers, who use their vehicles to provide services with minimum prices and short waiting times. P2P architecture is the common application framework (Tran et al. 2017). While it is a ridden location-the-work app, it processes payments, tracks distance, sets fare rates, and mediates the relationship between the company and its drivers (Gloss et al. 2016). The service technology platform organizes all ride activities and other processes. The price of an Uber ride is cheaper than a traditional taxi ride, although it may be higher during peak demand times (Gabel 2016). Due to surge pricing, transportation costs are higher during rush hours. Its core value is a reduction of search and transaction costs for both drivers and passengers (Blystone 2020). The amount of time or miles that a passenger travels in a certain period is used to calculate the price for capacity utilization. The only cost that must be taken into account is the cost of transportation because every economic agent is aware of the costs of all potential services. Customers can view the nearest driver and their ratings on mobile devices thanks to the innovative system (Kavadias, Ladas, and Loch 2016). Based on client reviews, which enable better rides, the driver's pay is determined.

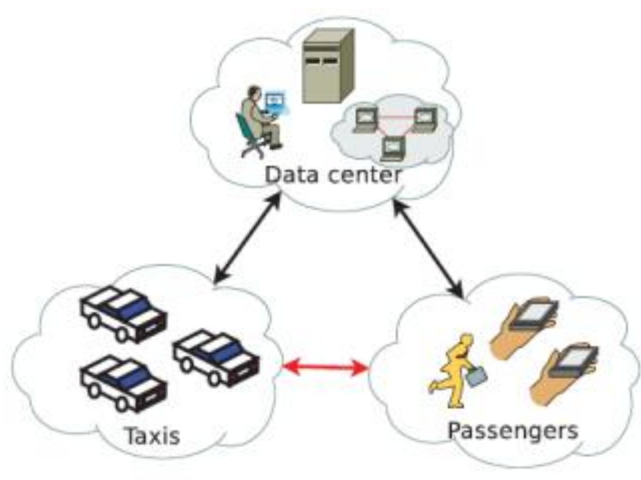
Drivers would face lower entry barriers into the driving market while having more convenient working hours than taxi companies. A user requests a vehicle through the mobile application that is provided by Uber, while the algorithmic ratings select a suitable driver. While the car contacts the user to perform the service, the application provides complete information about the user as well as the position, price, and route of the vehicle. As the data centers solely offer registration and management, the user, and cars function as peers. The difference between a typical taxi and the Uber taxi service model is determined by how requests are distributed to drivers and partners. The taxi model is as follows:

FIGURE 2.9: TRADITIONAL TAXI SERVICE MODEL (TRAN ET AL. 2017)



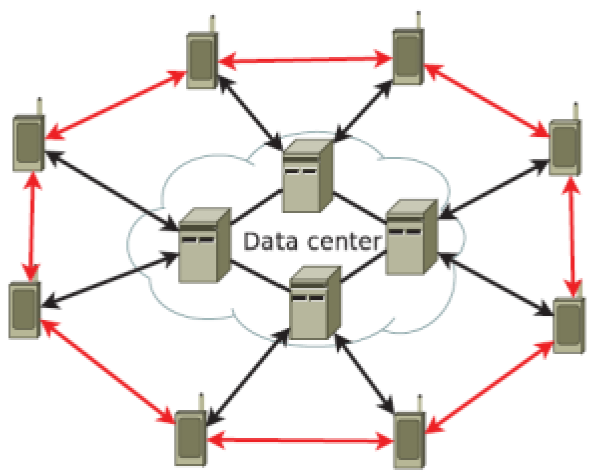
Regular taxi service, as seen in the diagram above, is based on a dispatch service that coordinates customer requests for suitable transport. Uber's model is as follows:

FIGURE 2.10: UBER TAXI SERVICE MODEL (TRAN ET AL. 2017)



The flowchart above depicts Uber's business strategy, which is built on a technology service platform that matches clients with available taxis. A P2P network is a collection of networked computers and mobile devices that peers can act as both client and server (while they share computing resources including file, storage, bandwidth, and processor power through consuming and provisioning services). The distribution of the resources into indexed peers by a centralized P2P server. The network topology is centered around the data center which is shown below:

FIGURE 2.11: MOBILE P2P NETWORK TOPOLOGY (TRAN ET AL. 2017)



Based on the data center model described above, the search methodology uses a Distributed Hash Table (DHT) as an identifier to group identifiers of the same type in the same place (Tran et al. 2017). DHT is used by the service enterprise platform to schedule and organize rides. The main components of the P2P network are as follows (Tran et al. 2017):

i. User Management component (UM)-manages user accounts including service providers and consumers.

ii. Service Management component (SM)-manages services registered by users.

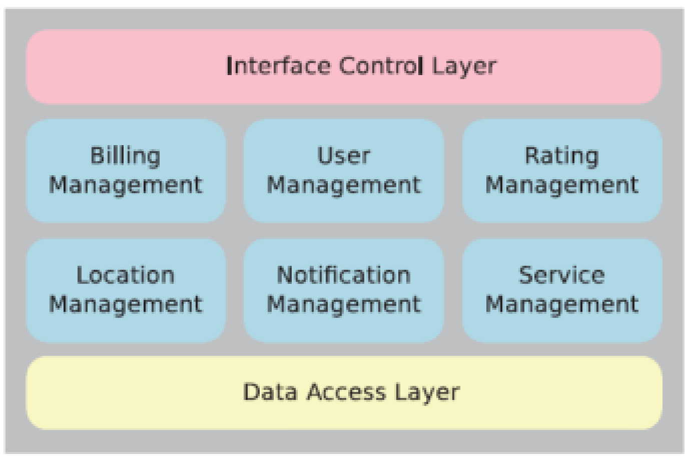
iii. The Location Management component (LM)-includes an application-oriented function that coordinates with third-party Application Program Interfaces (APIs).

iv. Notification Management component (NM)-manages notifications between the system and users.

v. Billing Management component (BM)-manages price, payment, and invoice issues as use services.

The interface has several architectural components for organizing data and executing the operations. The model below shows these layers:

FIGURE 2.3: COMMON APPLICATION ARCHITECTURE (TRAN ET AL. 2017)



The Interface Control Layer, as seen in the model above, coordinates and synchronizes all important business processes for the technological platform. While the requests which specify a pick-up time are pooled together given a time interval for static model settings, new requests can be combined and then assigned within the dynamic programming computing allocation. A queueing theoretic model is a strategic ridesharing platform model in which geographic locations are examined in regions with a high number of busy and available drivers (Banerjee, Johari, and Riquelme 2016). Each ride involves a driver picking up a passenger in one region and dropping him/her off in another. The surge and fair pricing models determine the immediate availability and pricing.

A fair pricing model should reduce the travel distance and maximize each driver's earnings based on the reward system (Asghari et al. 2016). This reward system checks the driver for new requests and selects the best driver through a matching process. This strategic action is based on the Auction-based Price-Aware-Real-Time (APART) ride-sharing framework (Asghari et al. 2016). A centralized server is responsible for matching and scheduling incoming requests, while the driver matching process the process through a spatiotemporal index. The server collects all the bids from candidate drivers and assigns the rider to the highest bidding driver. This process is based on the following conditions (Asghari et al., 2016):

i. The riders' waiting time constraint: The waiting time from the time the request until the driver arrives.

ii. The driver's capacity constraint: The number of riders in the vehicle cannot exceed the total capacity.

iii. Detour constraint: The maximum distance of every rider's trip should be less than the previous ride.

iv. The driver's and all riders' (the new rider and those already in the vehicle) monetary constraint: Each driver has a unique profile that allows him to specify the cost of service.

Uber is a great crisis management case study where data analytics is used during the pandemic for more efficient and safe services.

2.4 COVID-19 Pandemic Case Study

The CoV is a large family of positive single-stranded RNA viruses that are involved in respiratory, enteric, hepatic, and neuronal infectious diseases (Reguera et al. 2014). Public awareness about COVID-19 centered on the biological, epidemiological, and medical aspects of the coronavirus disease. The modern functional approach should be based on a healthy relationship between politics and epidemics to observe the current pandemic scenario of COVID-19. The sustainability of the relationship that humanity has with the natural world and the political relationships has been threatened, in such a way that an alternative approach with a healthier sense of public cohesion would be ideal. The imbalance between political states, nations' concerns about public health, fear, and panic would also trigger an economic crisis globally (Aaltola 2020). Global healthcare policies must be acted upon to establish consistent communication between countries and their citizens to resolve the virus outbreak.

Epidemic intelligence is the early identification, assessment, and verification of potential public health risks, with surveillance techniques for the automated and continuous analysis of unstructured free text or media information available on the Internet from social media, blogs, news, official sources (Bello-Orgaz, Jung, and Camacho 2016). Text mining techniques are applied to detect words related to diseases or their symptoms in published texts, while regression models are utilized to assess disease outbreaks. Twitter is an important tool to identify such events with global positioning ability. Internet News and online discussion can be alternative healthcare information sources for detailed local and near real-time data on disease outbreaks, complementing global event-based outbreak information such as Global Public Health Intelligence Network, and HealthMap (Keller et al. 2009). Surveillance systems are part of healthcare management that are used for the early detection of disease activity. Crisis communication refers to the process of exchanging information and opinions on a crisis, as well as the coordination of resources such as equipment, personnel, and information to avoid or mitigate harm and to coordinate resources during a crisis. Social media is used as a situational awareness tool, a communication tool, and as a platform for dynamic interaction. During a crisis, collaborative content-sharing media is employed for information exchange (Denecke and Atique 2016). Online discussion is another alternative information source for detailed local and near real-time data on disease outbreaks, complementing global event-based outbreak information such as Global Public Health Intelligence Network, and HealthMap. The user interface and visualization are based on the input signal generation within the event-based intelligence networks.

Technology is an important factor track infectious diseases. The semantic relationship and comparisons can be categorized in an eight-topic model (Dong et al. 2020). These are clinical characterization, pathogenesis research, therapeutics research, epidemiological study, virus transmission, vaccine research, virus diagnostics, and viral genomics. This framework is based on an adapted platform that gives a real-time interpretation of health status globally (Choi et al. 2016). Countries around the world can connect to it as part of ongoing updates. The Infectious Disease Biomarker Database (IDBD) is based on the biomarker indicators which represent therapeutic responses and monitoring activities allowing the users to link infectious diseases or pathogens to protein, gene, and carbohydrate biomarkers using search tools (Yang et al. 2008). Each geopolitical location can take preventive measures to protect its citizens and sustain them. Sharing economy platforms and other sectors are using this real-time data to manage their operations.

Web services are functional components that process input and output through a service architecture that supports the required operations and communication modes. The main goal is to introduce web services to represent data sources that establish a standard abstraction over the exact mechanism used to retrieve data. European Bioinformatics Institute, GenomeNet, and Virginia Bioinformatics Institute are some of the web services in life sciences (Curcin, Ghanem, and Guo 2005). Web-based social media with the increased use of the Internet and the increase in public participation in online forums and blogs provides valuable health information. The rapid identification of an outbreak of an infectious disease is essential for the effective development of public health responses. Social media and web-based models can track infectious disease trends to figure out whether an automated analysis of trends in Internet searches in real-time to predict, observe, and minimize the harm caused by outbreak events. (Yang, Horneffer, and DiLisio 2013). Web Services Description Language (WSDL), Simple Object Access Protocol (SOAP), and Universal Discovery and Description and Integration (UDDI) are three standard frameworks for representing and manipulating web services in Life Sciences (Curcin, Ghanem, and Guo 2005). WSDL is an Extensible Markup Language (XML)-based standard for describing web services and specifying their parameters, inputs, and outputs. SOAP maps the abstract services described in WSDL to their concrete implementations where the objects are passed to and from web services and enabled to be executed by the remote client. UDDI enables Internet Service Providers to publish their services for the community to browse and look up specific services.

The temporal, content dependence and event reference indicators are used to identify to what extent a component event is dependent on another in the evolution of a target event (Cai et al. 2019). The temporal Event Map represents the whole picture of an event's evolution or development by showing dependence relationships among events, and by allowing users to view the target event where experiments are conducted on a real data set. Contact tracing to capture the transmission of the virus and statistics to forecast how far the disease spread is part of this. Dynamic querying features with Advance Querying Tool allow users to develop, investigate, save, and share complex case definitions in the automated disease surveillance systems that notify users of increases in the prevalence of reports in syndrome categories (Hashemian 2010). It allows users to view patient-level data related to those increases. The mapping algorithms can be changed based on the generical dataset of each country. Reference-based mapping, short sequence classification, and de-novo assembly are the main dimensionality reduction methods with analytical performance retained (Tapinos et al. 2019). The accuracy of the results is crucial for the risk management of the crisis.

Social media and web search studies would identify individuals within a network who should be targeted for vaccinations to prevent the spread of disease. Sharing economy service platforms are strongly connected to social media networks to operate. Social network patterns are indicators of disease progression among the entire population by data mining of these sources. The search methodologies of Web searches, blog postings, social networks, and geographical information systems should be considered useful supplements to epidemic intelligence tools (Yang, Horneffer, and DiLisio 2013). Mapping a whole network to identify central individuals who might be monitored for infection near the center of a social network. An ideal alternative is friendship-nominated networks that do not require the detection of global network structure. The mathematical modeling of betweenness centrality would play a role in the early detection of an epidemic as a rapid warning (Christakis and Fowler 2010). Contact tracing is a technique that can be applied over an econometric model to determine the spread. Real-time surveillance, such as Google searches, provides extra information for the prevention of the spread of infectious diseases with the ability of quick identification (Medlock and Galvani 2009). There are modern technological innovations to help rule out the transmission of the virus. A geographical information system (GIS) is a technological tool that can be used to locate a potential epidemic and make intelligent decisions to handle healthcare decisions (Yang, Horneffer, and DiLisio 2013). GIS is also an important part of the sharing economy platforms. Artificial algorithmic models can be created that divide societies into groups with high and low risks of carrying a transferable disease. Based on the epidemic-populated data sets, a mathematical model can be used to identify emerging outbreaks that can happen, however dependence on these models should be avoided to avoid making insufficient decisions (Locklear 2018). Worse-case and best-case scenarios are established to manage systemic risk. Sharing economy can locate high-risk areas and take necessary safeguards using predictive analytics.

A decision-support tool using Artificial Intelligence and Predictive Analytics is an important tool to identify which cases will escalate to critical illness, by using pattern recognition techniques for close monitoring and intervention. The pandemic model should be realistic based on change day-to-day where the measures are aided by data science, analytics, and epidemiology. The exponential growth of the cases may be delayed by the prevention steps (Anadiotis 2020). Google and Apple joined in laying out a protocol for tracking the coronavirus outbreak, which will be based on an automated contact-tracking system (Brandom 2020). The common framework will be available as an app on the mobile operating system to give a warning when a person receives a positive diagnosis due to being near another phone whose owner was infected previously. The diagnosis will be a permissible action when the phone owner opts to send his/her ID code to a central database. The central database checks the database to see whether any of the codes in its log match the IDs in the database, and the owner will get a warning of exposure based on the outcome. The person's anonymity would be protected due to eliminating personal information and designed to be used as a public surveillance strategy by government health officials.

To reduce the likelihood of virus transmission during the pandemic, certain protocols and the optimal data science solution must be used. These are considering potential actions to deviate from COVID-19, choosing action triggers for the decision criteria, choosing the minimum quality of information sources that can serve as valid triggers, gathering information from high-quality sources, and a proper strategy for the execution based on a triggered action (Kozyrkov 2020). Sharing economy operatively and healthcare policies are established on these principles to protect the employee and the customer, as well as manage their operations. The daily insights from data analytics that processes real-time information would be part of this phenomenon. Uber and Airbnb use these insights for safe and healthy operations daily.

CHAPTER 3 METHODOLOGY

Sustainability is recognized for taking action to alleviate environmental issues, such as the COVID-19 epidemic. Companies need to adjust their existing operations and decision-making capability to stay competitive. The financial performance linked to each company's strategy affects sustainability factors, and the growth prospects are limited by managerial decisions based on financial and healthcare constraints. The COVID-19 pandemic changed the corporate and work settings to avoid the transmission of the virus. Sharing economy service activities were re-designated for safe and healthy business operations. That includes answering global health objectives in a financially stable corporate environment. To remain sustainable while adjusting business operations to environmental issues during crisis management, an optimal viable system model needs to be investigated. The suggested changes may include the modifications in each company's hardware and software system, as much as each Board of Directors enforcing capability. The integration of sustainability in the information systems is required to be evaluated by the existing frameworks, meanwhile, the system models are under constant observation to challenges of the environmental factors. As sharing economy services continue to operate during the COVID-19 crisis, data analytics is a component of these information systems that respond to and adapt to essential adjustments under crisis management.

3.1 RESEARCH QUESTIONS AND HYPOTHESIS TESTING

This dissertation study aims to analyze the role of data analytics in sharing economy during the COVID-19 pandemic as a crisis management tool. Therefore, the following research questions are formulated.

3.1.1 Research Questions

There have been studies about data-driven decision-making as a crisis management tool that utilizes data analytics in the past, but there is a lack of information on how data analytics was used as a risk management technique in the sharing economy. The following research questions are formulated to determine the role of data analytics as a crisis management strategy for sharing economy during COVID-19:

Research Question #1: What was the economic performance of the sharing economy during the COVID-19 pandemic?

Research Question #2: How was data analytics used in the sharing economy during the COVID-19 pandemic?

a) What were the consequential advantages of data-driven decision-making during the COVID-19 pandemic?

b) What were the consequential disadvantages of data-driven decision-making during the COVID-19 pandemic?

Research Question #3: What preventive steps can be taken to improve data analytics as a crisis management tool in a post-pandemic world of sharing economy?

3.1.2 Research Scope

During the COVID-19 pandemic, this study focuses on the application of data analytics for crisis management in the sharing economy. Although there is some scholarly research about crisis management in the sharing economy since the pandemic started, studies on factors affecting data-driven decision-making are limited. Data Analytics is an important part of business operations and has become an important asset for the sharing economy. The research utilizes content analyses and data analysis methods to investigate the role of data-driven decision-making as a crisis management tool. Predictive analytics is used as a model to view and manage service operations. The economic data is the financial performance of sharing economy services during the crisis. It is based on the intraday stock price data which is collected from Yahoo! Finance website and a predictive model is presented for each company to view the economic outcome. The trend data is investigated by bibliographic coupling and keyword occurrence of the research articles where they were extracted from the Web of Science (WoS) database by using selected keywords. These keywords are COVID-19, crisis management, and data analytics-related. The action process factor is the expectation of the sharing economy services to improve their crisis management capabilities based on data analytics. It is discussed and suggested by the coding schema of thematic subjects from the bibliographic coupling and keyword analysis. The optimality of better business operations is investigated to improve the risk management strategy and increase customer confidence. The research is limited to the role of data analytics as a crisis management tool for the sharing economy view based on collected financial data, keywords analysis, and bibliographic coupling of the scientific articles that are retrieved from the WoS database platform.

CHAPTER 3.2 METHODOLOGY

The dissertation aims to determine the role of data analytics in sharing economy as a crisis management tool during the COVID-19 pandemic. The research objective was evaluated using qualitative and quantitative research methods. The qualitative research method depends on the data collection process to support the study objective and confirm the quality of the research (Oun and Bach 2014). The methodology was based on a triangulation method that utilizes content analysis and statistical valuation methods. The preferred methods were regression analysis, bibliographic coupling, and keyword occurrence analysis to answer the research questions. The content analysis method enables researchers to analyze the context unit by applying rules (Frankfort-Nachmias, Nachmias, and Deeward 2015). These rules were established to construct a scholarly research study. The data analysis involves searching for patterns to discover important factors for answering research questions (Bogdan and Biklen 1982). Pattern recognition is an advanced technique that is used in quantitative methods as well as content analysis. These context units are groups of words with similar meanings in the content analysis (Weber 1990). The same set of statistical data can create a data cluster. These two types of analogies can be used as a pattern recognition that replicates a predictive statistical scenario and contextual meanings in the thematic (including keywords) groupings. This was applied to answer research questions and the research objective.

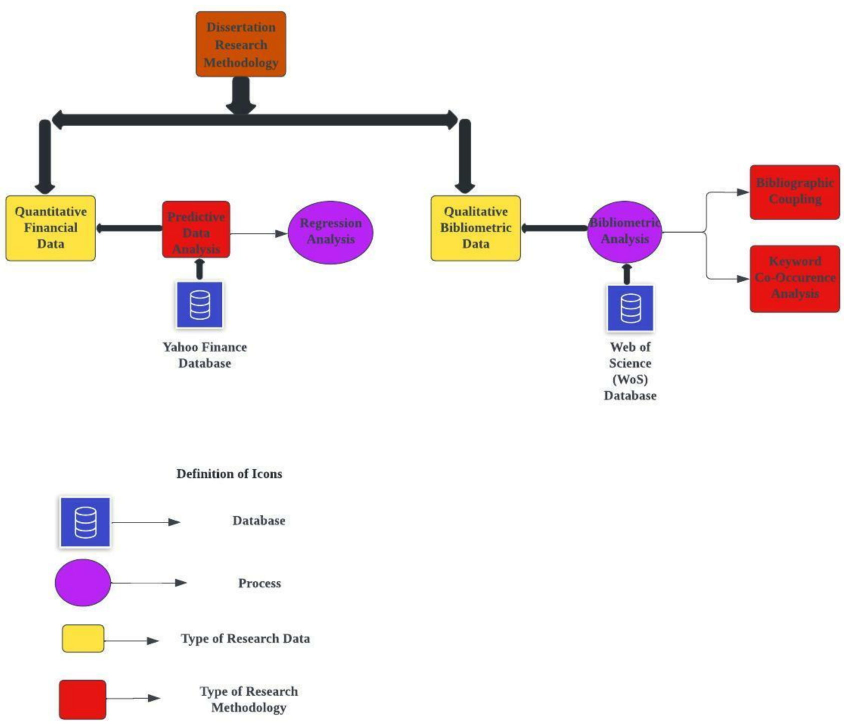
3.2.1 Method Selection and Justification

To address the research objective and examine the function of data-driven decision-making as a crisis management tool, a hybrid method combining quantitative and qualitative techniques was selected. The statistical and qualitative methods are widely used in library and information science in several studies. Data analysis models were constructed to determine the economic performance of the sharing economy during the pandemic. Predictive data analytics software, RapidMiner, was chosen to apply regression analyses. To observe factorization depending on other attributes, the target attribute was chosen. Although the data model can show us a financial forecasting scenario during a pandemic, there was a need for a deeper understanding of the contribution of data analytics to sharing economy as a risk management tool. Bibliographic coupling and keyword analysis methods were chosen to answer the effects of data analytics on sharing economy. The data and publications were found using a keyword search in the WoS database. To examine the entire benefits and limitations of data-driven decision-making when used as a crisis management tool, five different keyword search orderings were developed. Each keyword arrangement was chosen to represent various facets of sharing economy service crisis management. The articles' full texts and cited references served as the basis for the keyword occurrence count, which was selected in conjunction with bibliographic coupling to identify in-depth observation of the study objectives.

3.2.2 DATA COLLECTION DIAGRAM

The dissertation study data collection consists of quantitative and qualitative data to answer the research questions. The data collection diagram was created by using the Lucidchart visualization software, which can be reached at http://lucidchart.com. The detailed research methodology diagram is as follows:

FIGURE 3.1: PATTERNS OF DATA COLLECTION METHODS



Bibliographic coupling and keyword analysis are examples of qualitative data approaches, as illustrated in the model above, whereas predictive modeling, which is based on regression modeling, is an example of a quantitative method. The dataset was imported into the RapidMiner program after intraday financial data was downloaded from the Yahoo Finance Database. Under the Linear Regression Method, the target attribute is set to the Adjusted Closing Price. Dataset was partitioned under the Cross-Validation technique, which divides the population into training and testing samples. Incorporating other independent factors such as date, open price, high price, low price, closing price, and share volume, the linear regression technique was used to analyze the adjusted closing price as a dependent variable. The modeling error was also measured using performance indicators like a relative error.

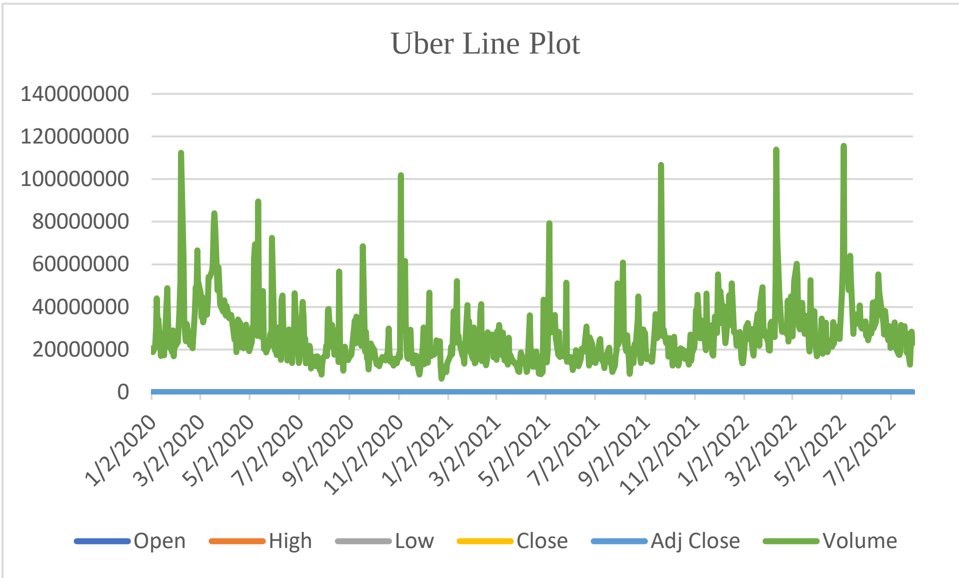
Peer-reviewed scientific articles were downloaded from the WoS database and computed with VOSViewer bibliometric software. The distance between the documents is observed as the relatedness of the articles. The strength of a link indicates the number of citations two documents (articles) in common, known as bibliographic coupling, or the number of articles that two researchers have co-authored, known as co-citation analysis (Van Eck and Waltman 2014). The most illustrative factoring impact inside scientific publications was portrayed as two articles citing one other article as the strength of the link in the bibliographic coupling approach. The most common keywords in every article are thought to help address research issues and include all keywords, not just the authors' chosen ones.

3.2.3 Data Analysis of the Sharing Economy

Financial information was examined as a component of safe and effective operations. The sharing economy's statistical evaluation served as the foundation for the data analysis technique. It is a financial performance prediction model for Uber and Airbnb. Each model represents the financial performance of Uber and Airbnb through a linear plot. The information is taken from the Yahoo! Finance website, whose timeline during the pandemic was made available to the public. Timetable for sharing economic real-time intraday financial stock data from 2020 to 2022. The data sheet was acquired from Yahoo! Finance in Microsoft Excel.

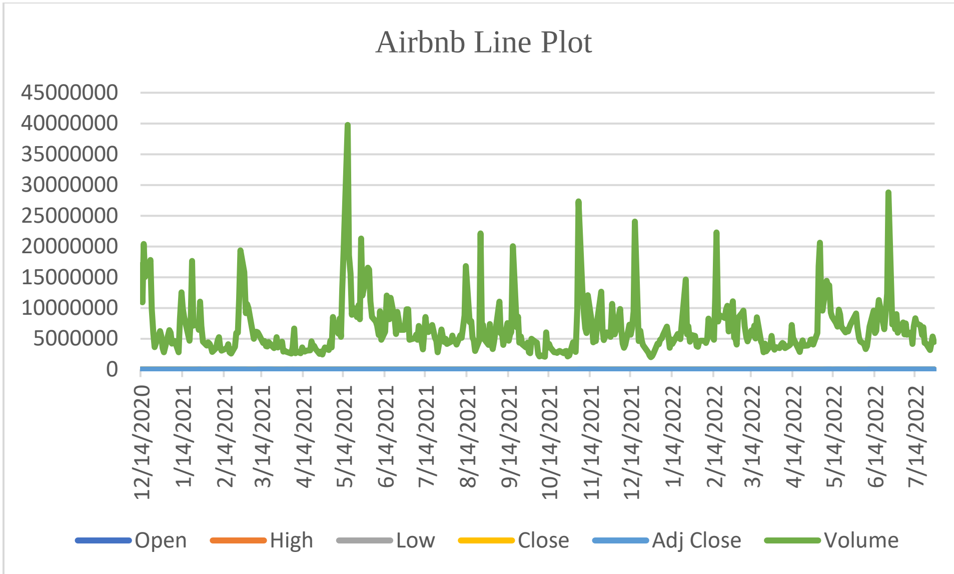
Data for the intraday price of Uber's shares is available between January 2, 2020, and July 29, 2022. The financial model that is based on the historical data shows the timeline as a horizontal X-axis and the number of shares that were traded daily as a vertical Y-axis on a cartesian coordinate space is as follows:

FIGURE 3.2: LINE PLOT FOR THE UBER ADJUSTED CLOSING PRICE DEPENDING ON SHARE VOLUME



In the model above, the Y-axis represents the volume of shares, while the X-axis represents the date. Airbnb, intraday stock price data is between Dec 14, 2020, and July 29, 2022. Similarly, line chart modeling for Airbnb is as follows:

FIGURE 3.3: LINE PLOT FOR THE AIRBNB ADJUSTED CLOSING PRICE DEPENDING ON SHARE VOLUME



The Y-axis in the model above represents the number of shares, and the X-axis shows the date.

The primary method for making predictions is regression analysis. Regression analysis is one of the most used techniques that allow researchers to analyze relationships between one independent and one dependent variable. The technique can provide the necessary information if independent variables have a relationship with the dependent variable, the strength of the independent variables' effect on the dependent variable, and as well forecasting ability for future changes (Mooi, Sarstedt, and Mooi-Reeci 2018). For example, by predicting the changes in the intraday of a stock price, adjusting the volume of the shares, increasing the number of shares, or decreasing the number of shares, we can calculate the effect on that stock price. Mathematically speaking, regression models are generally represented (Mooi, Sarstedt, and Mooi-Reci 2018):

$$y = \alpha + \beta x + e$$

Y represents the dependent variable on the XY coordinate space that we are trying to explain, and α is the intercept of the regression model that indicates what the dependent variable would be if all the independent variables were zero. X is the independent variable on XY coordinate space. β is the coefficient of the independent variable X that represents the gradient of the line. It is also known as a slope, which can be directed in either a negative or positive direction. Finally, the symbol “e” denotes the error of the equation, which is the difference between the regression line (prediction regression) and the actual observation. Tracking error is usually calculated when scientists compute the forecasting models to observe the differences from the actual observation.

First, the financial results of Uber and Airbnb were imported into Microsoft Excel, and then computations involving lognormal pricing were carried out. Loglinear returns, which represented the relative change in value from the day before, were produced. To calculate an accurate reflection of each stock's growth, a method based on the financial log-normal stock pricing model was developed (Sharpe, 2004). That represents the stock's relative move from the day before. Instead of using actual stock prices, log-normal pricing is used to track the pace of change based on its value. The growth rate of stocks may be calculated more easily than daily price variations. The formula is as follows:

Let S be the stock price and t ($t \geq 0$), as a variable, is the number of days, where

S(t) = present-day indexed stock price

S(t-1) = previous day indexed stock price

Thus, log (St / St-1) is the corresponding rate of stock growth between the present and the previous day (Sharpe 2004). The log-normal growth rates were calculated first, and then the log-normal stock prices were imported into a single datasheet. Their scatter plot model's financial performance throughout the crisis was examined.

To forecast the adjusted close price and daily volume of shares traded, a linear regression model is used. To begin with, a spreadsheet file containing financial data is imported into the RapidMiner software system for first processing. The Excel files from Uber and Airbnb are read as CSV files, where the system looks for any missing values or properties. Their linear regression models were computed under Cross Validation Methodology, where the datasets were divided into training and testing samples. Adjusted Closing Price was selected as the target attribute. Other independent variables are date, open price, high price, low price, closing price, and share volume. Utilizing RapidMiner's performance operator, the modeling tracking error was calculated.

3.2.4 Bibliographic Coupling and Co-Citation Analysis

The mapping of a vast number of bibliometric networks, ranging from networks of citations between publications or journals to networks of co-authorships between scholars or networks of co-occurrences between publications, is the visual display of bibliometrics. (Van Eck and Waltman 2014). A bibliometric network is composed of nodes and edges. Nodes contain publications, journals, researchers, and keywords. The edges connect two nodes, and the most common forms of relationships are citation relationships (among researchers and journals), keyword co-occurrence connections, and co-authorship relationships. Bibliometric networks are weighted networks in which the edges show the strength of the relationships as well as the relationship itself (Van Eck and Waltman 2014). Keyword analysis, citation analysis, bibliographic coupling, and co-citation analysis are bibliometric types of analyses that are used in library and information science. Bibliometric analysis methods are proven to be effective methods for identifying changes in research topics. The direct citation method, as opposed to co-citation and bibliographic coupling, might result in networks with a limited number of edges

(Van Eck and Waltman 2014). This may result in a defective or lost inquiry about the result. Bibliographic coupling and co-citation analysis methods represent co-occurrence networks as authors and journals as the unit of analysis for identifying co-occurrence networks (Chang, Huang, and Lin 2015).

Bibliographic coupling is the connectivity of objects that are weighted based on the number of references they share (Sahu 2021). The main principle is to check the relatedness of two papers, and that they have several common references. If a third publication is cited by both publications, they are considered bibliographically connected (Kessler 1963). The connective coupling is based on the number of citations that they receive which provides similarities between these two articles. The strength of their connection is measured by the number of common references (Marshakova 1981). It's the opposite of citation. It's about the overlap in publication reference lists. The stronger the bibliographic coupling relationship between two publications, the greater the number of references they have in common (Van Eck and Waltman 2014).

If a third publication references two other publications, they are considered co-cited. (Van Eck and Waltman 2014). The degree of resemblance between publications is determined by common references. A co-cited analysis is based on the indexed data where co-citation is the degree of relatedness that is based on the number of times they are cited together (Sahu 2021). In these research methodologies, relationships between referenced references, sources, and co-authors are typically examined. The greater the number of publications that cite two publications, the stronger the citation relationship between the two publications (Van Eck and Waltman 2014). Common references may point to an essential topic that could aid in determining or changing the course of the investigation. A two-step process can be established to satisfy the co-citation analysis (Marshakova 1981): a) dividing the articles into cited (basic) and citing (prospective) documents; b) the number of citations to a basic document "a" is called its volume, and the number of references in a prospective document of "x" is called its weight; c) the calculation of the strength of the connection between basic documents "a" and "b." In other words, "a" is a variable called the volume that represents the number of citations to a basic document that we have, and "x" is a variable called the weight that represents the number of references in a prospective document. The strength of the connection between two documents is computed by using these variables, which are reflected in the software model. Suppose we have documents called "a" and "b" as basic documents, as well as "c" and "d" as prospective documents. If both basic documents are cited by the prospective documents, then documents "a" and "b" have a co-citation strength of two. The formation of clusters of co-cited documents and the assignation of scientific articles to the co-citation clusters are part of this process (Boyack and Klavans 2010). Articles in a cluster indicate many shared references. Co-occurrences of keywords can be retrieved from the full record, title, and abstract of a publication (Van Eck and Waltman 2014). The number of keywords is a crucial aspect in the analysis and evaluation of the pandemic's consequences.

The WoS database has been deployed to retrieve the bibliographic data of publications about COVID-19, sharing economy, data-driven decision-making, data analytics, and crisis management between the years 2020 and 2022. The chosen keywords were "COVID-19," "Data-Driven Decision Making," "Data Analytics," "Sharing Economy," "Uber," "Airbnb," "Crisis Management," "Black Swan," "Risk Management," and "Value at Risk." The chosen procedural methodology was based on Fellnhofer's "Visualized Bibliometric Mapping on Smart Specialization: A Co-Citation Analysis" as described below (Fellnhofer 2018):

a) First, data and document collection were established where the dataset contains these keywords in the topic or title from the WoS database. Their full records and cited references were downloaded as a tab-delimited file.
b) Second, the characteristics of this collection are described.
c) The frequency of bibliographic coupling and co-citation analysis has been determined and tables were created to show the documents.

The coding categories are mutually exclusive and exhaustive, which captures variations using the minimum number of categories (Frankfort-Nachmias, Nachmias, and Deeward 2015). A common theme coding scheme represents the bare minimum amount of relevant common subject issues. The research employed the bibliographic coupling methodology to examine common thematic research fronts and crucial pandemic and research subject matters, and the keyword count methodology to examine contributing factors and crucial research factors. These solid findings helped to address Research Questions #2 and #3.

3.2.5 Visualizing Bibliometric Mapping

There are three popular approaches for visualizing bibliometric networks. These are the distance-based approach, the graph-based approach, and the timeline-based approach (Van Eck and Waltman 2014). Each strategy addresses a different viewpoint. Alternative visuality methodologies are circular visualizations (Borner et al. 2012), and self-organizing maps (Skupin, Biberstine, and Borner 2013). In a bibliometric network, the distance between two nodes is expressed as the relatedness of the nodes, where the nodes are arranged in a two-dimensional space. Nodes are placed in a two-dimensional space in the graph-based approach, and edges are presented to illustrate node-relatedness. The graph-based approach is suitable for visualizing small networks because of the limitation of not showing many edges in a bigger network. In the timeline-based approach, each node in a bibliometric network can be linked to a given point in time. It's good for showing publication networks based on publication dates. One dimension is a two-dimensional space that represents time, while the other represents node-relatedness. The point in time to which a node is associated is used to calculate its location in the time dimension. The relatedness of nodes to other nodes can be used to calculate the location of a node in the other dimension.

The main software tools for analyzing and visualizing the bibliometric networks are CiteSpace (Chen 2004), Sci^2 (Sci2 Team 2009), and VOSViewer (Van Eck and Waltman 2010). CiteSpace shows how the bibliometric network is evolving, relying on dynamic visualizations. It uses graph-based and timeline-based visualizations. Sci^2 is a general software tool to analyze bibliometric networks, where it relies on external software tools. VOSViewer provides distance-based visualizations of bibliometric networks, where the edges are not displayed. The distance between two nodes is the relatedness of the nodes. HistCite (Garfield, Pudovkin, and Istomin 2003; Garfield 2007) and CitNetExplorer (Van Eck and Waltman 2014) are two software tools for analyzing direct citations. HistCite takes WoS output files as input, and several bibliographic data are shown based on several statistics on publications, researchers, and journals. CitNetExplorer offers extensive and detailed visualization capabilities in a publication citation network.

3.2.4.1 VOSVIEWER BIBLIOMETRIC VISUALIZATION SOFTWARE

The co-citation map and journal citations are the faces of the scientific community. VOSViewer visualizes any sort of bibliometric network using a distance-based technique (Van Eck and Waltman 2014). Undirected networks are those that are based on direct citation relationships. The construction of a two-dimensional space in which closely connected nodes are adjacent to each other. Its visualization strategy is to highlight the relationship between the nodes by visualizing similarities. In the network representation, each item is given a label and, by default, a circle (Van Eck and Waltman 2011). While the color of an object is defined by the cluster to which it belongs, the size of an item is determined by its weight. Two variations of the density visualization technique are density and cluster density visualization. (Van Eck and Waltman 2011). In the item density visualization, things are represented by their labels, while the cluster density visualization is only accessible if items have been assigned to clusters. A default network cluster is created, which assigns a group of nodes that are closely related. A resolution parameter is used to calculate the number of clusters, with each node in a network belonging to exactly one cluster. Colors are used by the software tool to determine which cluster a node belongs to.

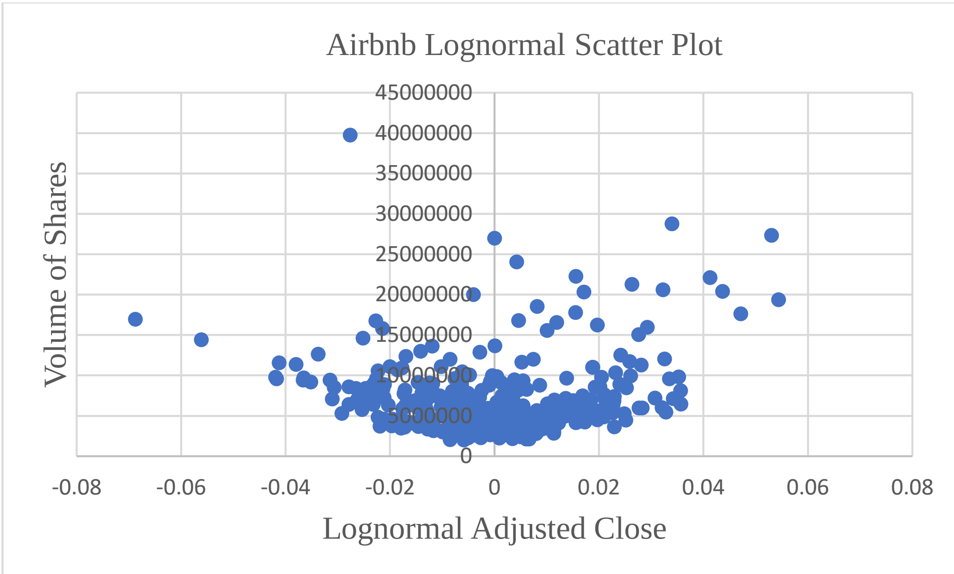
Full counting entails giving each co-author of a co-authored publication a full weight of one, indicating that the total weight of the publication is equal to the number of authors (Perianes-Rodriguez, Waltman, and Van Eck 2016). Each publication receives an equal number of numbers after full counting. A co-authored publication is weighted fractionally for each co-author, with the publication's overall weight set at 1 (Perianes-Rodriguez, Waltman, and Van Eck 2016). This is known as fractional counting, where each publication has the same overall weight during fractional counting. An article that cites both a low-cited research paper that addresses a related topic and a highly cited review article that provides a thorough summary of the literature and contains various issues that are only loosely related to the topic. Fractional counting can lead to more optimized results for bibliographic coupling and co-citation analysis. It is the preferred methodology in this research to address the research objective.

VOSViewer employs a standard normalizing method that is linked to relatedness strength. The degree of connection is reflected in the link's strength, which also determines a key aspect of the dissertation study. Following the import of the published datasets into the VOSViewer software system, several computational operations were carried out using approaches for keyword counts and bibliographic coupling. For these techniques, three citations were chosen as the bare minimum. Bibliographical coupling coding system for the top 15 scientifically related articles. The 15 most often used keywords were chosen as the keywords. For the investigation of the research objectives, various significant factors were contained in each bibliographic and keyword count table.

3.2.6 Dissertation Pilot Study

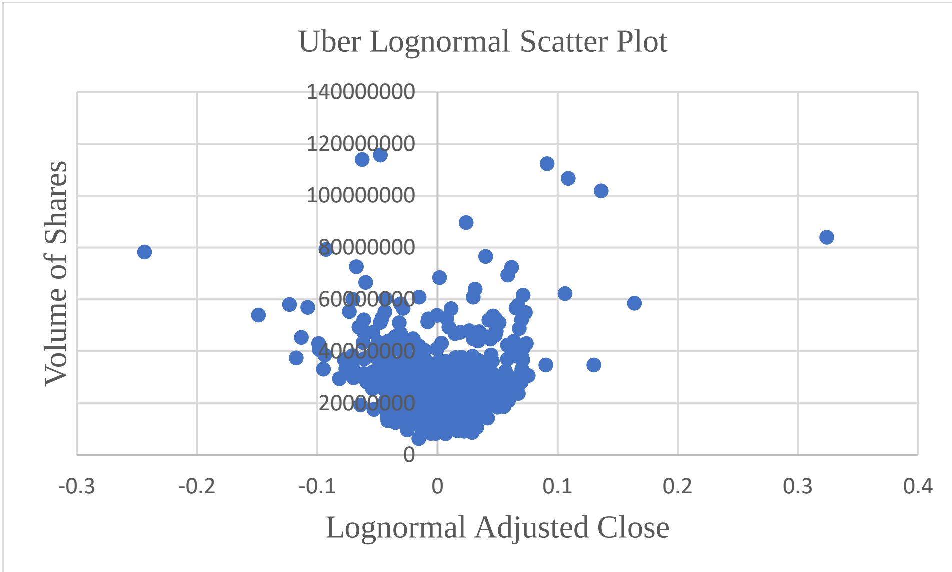
A pilot study was conducted using Microsoft Excel, VOSViewer, and the WoS database. Excel computed the log-linear returns for the adjusted closing price, and a scatter plot was created using those results. The volume of shares on the Y axis, which reflects changes in the incremental value, and the lognormal adjusted closing price on the X axis, which represents the variables, are shown in the models below.

Figure 3.4: Airbnb Lognormal Scatter Plot



The modified closing price is shown in the model above in very small incremental adjustments based on the share volume that was traded. That illustrates the degree of nearby changes during the epidemic, which is a cautious and conservative approach. As seen in the model above, an incremental drop in the adjusted closing price causes the formation of a cluster as the daily traded volume of shares falls. Similarly, Uber's model is below:

FIGURE 3.5: UBER LOGNORMAL SCATTER PLOT

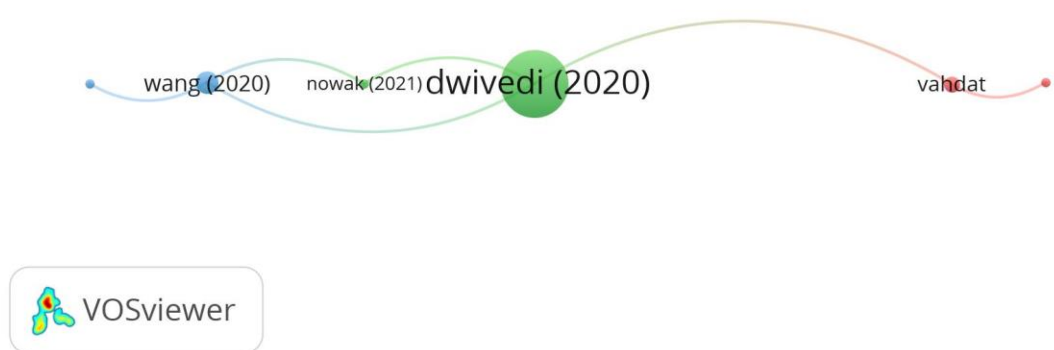


Based on the volume of shares traded, the model above depicts very small incremental changes in the adjusted closing price. That is a modest estimate of the degree of nearby changes during the pandemic. Based on the model, as the daily traded volume of shares decreases, an incremental change in the adjusted closing price results in the creation of a cluster. A loose symmetric link between the adjusted closing price and daily share volume of trading may be seen. The adjusted closing price and daily share volume of trade may show a loose symmetric connection in a scenario similar to Airbnb's lognormal model.

Articles were browsed and searched by using selected keywords. These keywords and keyword phrases were ‘COVID-19,” “Sharing Economy,” and “Crisis Management.” The timeline for publications was determined between 2020 and 2022 (present time). Forty-two articles were extracted by using these keywords under time constraints. These files were exported from the WoS database as a tab-delimited file and saved as a Microsoft Excel sheet. The pilot study tab-delimited file was imported VOSViewer for computation.

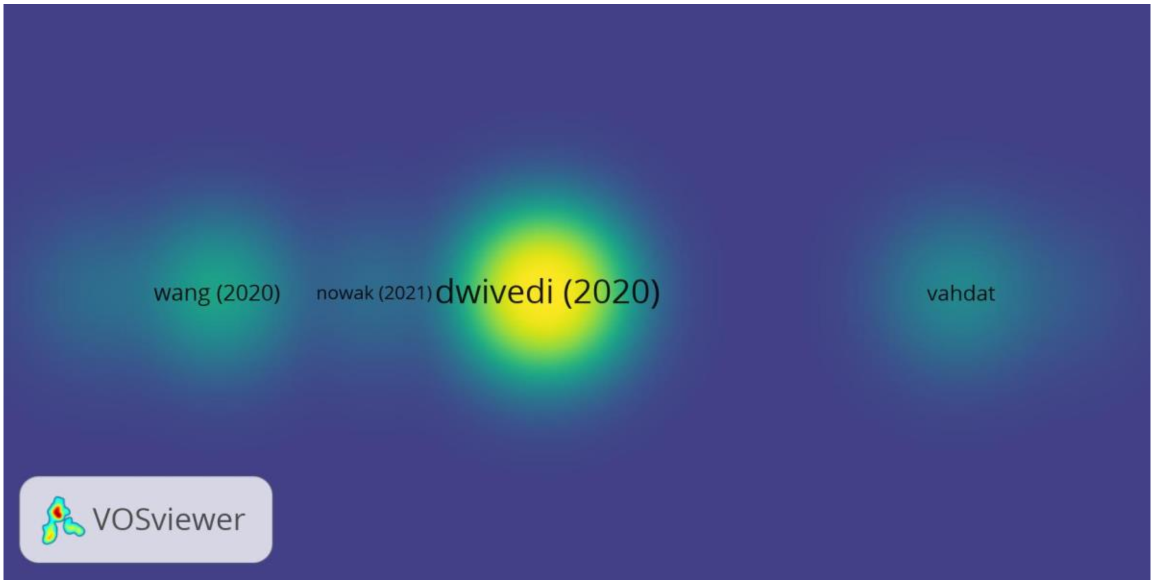
At first, the bibliographic coupling methodology was initiated by using the VOSViewer software tool. 20 documents were selected with a minimum of one citation (full counting) and the document with the greatest total strength was selected. Nodes terminology was determined to describe the journal articles, references, proceedings, and abstracts for software purposes. The images are as follows:

FIGURE 3.6: BIBLIOGRAPHIC COUPLING NETWORK VISUALIZATION (PILOT STUDY)



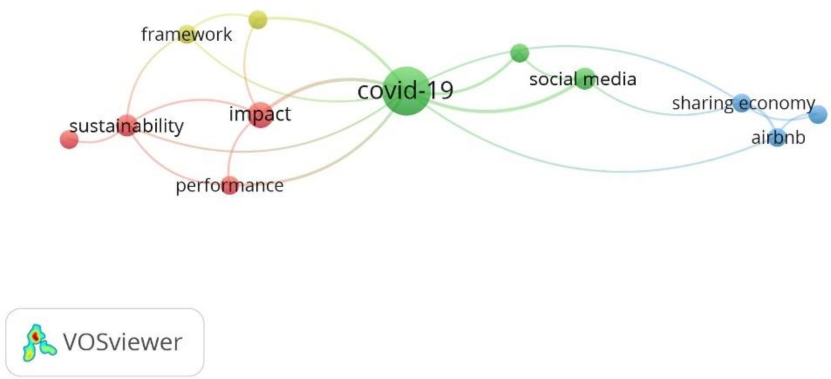
The visualization of the bibliographic connection network for the pilot study is shown in the model above. Bibliographic coupling density visualization is below reflects the density of the articles:

FIGURE 3.7: BIBLIOGRAPHIC COUPLING DENSITY VISUALIZATION



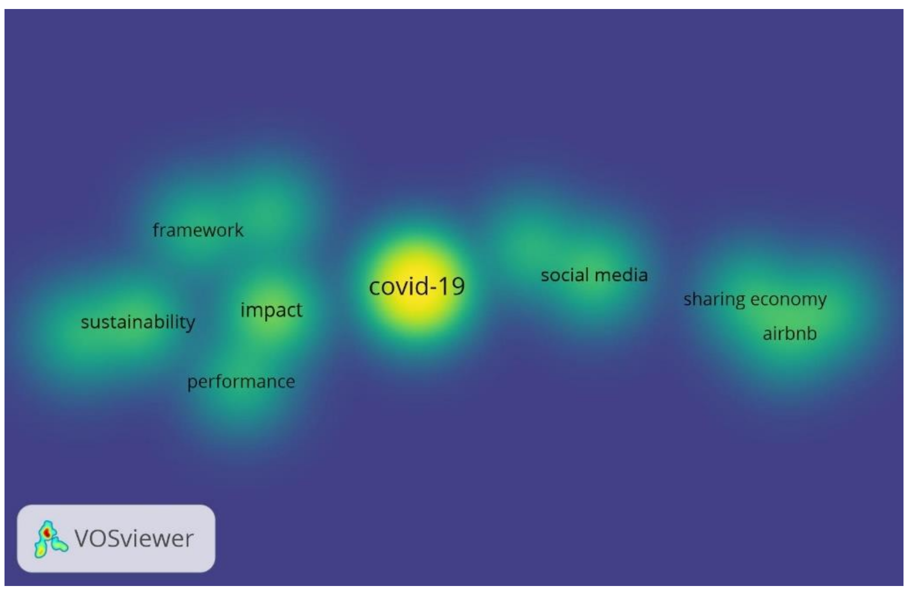
The visualization of the bibliographic connection density visualization for the pilot study is shown in the model above. The bibliographically coupled nodes were about the use of mobile communications at work and the role of technology in the management of human resources in the COVID-19 era. Other bibliographically coupled nodes were the impact of COVID-19 on information management research and practice, and misinformation and preventive measures during the early phase of the COVID-19 pandemic. At last, the keyword occurrence technique was applied to the same file, by using VOSViewer, with a minimum keyword repetition of 3. The images are as follows:

FIGURE 3.8: KEYWORD OCCURRENCE NETWORK VISUALIZATION (PILOT STUDY)



According to the model shown above, COVID-19, social media, the sharing economy, impact, Airbnb, sustainability, framework, and performance were the most often used terms in the articles. Similarly, the density visualization for the keyword frequency is below:

FIGURE 3.9: KEYWORD OCCURRENCE DENSITY VISUALIZATION (PILOT STUDY)



As can be seen in the model above, a cluster has been created around sustainability, impact, and performance. Another cluster has been created around social media, the sharing economy, and Airbnb. Sharing economy services and their sustainable framework's performance were affected by COVID-19 based on the pilot study and keyword search in the WoS database. The role of technology, predominantly mobile communications, played an important factor in the prevention of the virus in the workplace. Sustainable tourism was one of the most affected sectors with the greatest link strength in bibliometric analysis. The use of Geographical Information Systems and mobile app technology for contact tracking is a significant technique for identifying virus infection. It is obvious that technology had a significant part in the prevention of the virus in the workplace as well as the most sustainable workplace.

CHAPTER 4 RESULTS

4.1 PREDICTIVE DATA ANALYSIS OF SHARING ECONOMY

Excel spreadsheets containing financial intraday datasets related to the sharing economy were downloaded from the Yahoo Finance website. For computation, they were imported into the RapidMiner Data Analytics program.

4.1.1 AIRBNB DATA ANALYSIS

Airbnb, intraday stock price data is between Dec 14, 2020, and July 29, 2022. The dependent variable adjusted close price and prediction is based on the aggregate factorization of other independent variables. Linear Regression Analysis is applied to the dataset under Cross Validation, and its performance indicators are measured. The independent variables are Open Price, High Price, Low Price, Close Price, and Volume of Shares. The table below is showing the actual and predicted prices of Adjusted Closing Price:

TABLE 4.1: AIRBNB LINEAR REGRESSION - CROSS VALIDATION EXAMPLE SET

	Minimum Price	Maximum Price	Average
Adjusted Closing Price	89.080	216.840	156.744
Prediction (Adjusted Closing Price)	88.969	213.042	156.743
Open	88.800	216.240	156.799
High	91.460	219.940	160.615
Low	86.710	209.090	152.831
Close	89.080	216.840	156.744
Volume of Shares	1995400	39755000	6693345.966

The predicted adjusted closing price for Airbnb is comparable to the actual adjusted closing prices, as can be seen in the table above. Aggregate pricing is based on other independent variables (Open Price, High Price, Low Price, Date, and Volume of Shares). Performance metrics are shown below:

Performance Vector of Airbnb:

Root Mean Squared Error: 3.293 +/- 0.729 (micro average: 3.367 +/- 0.000)

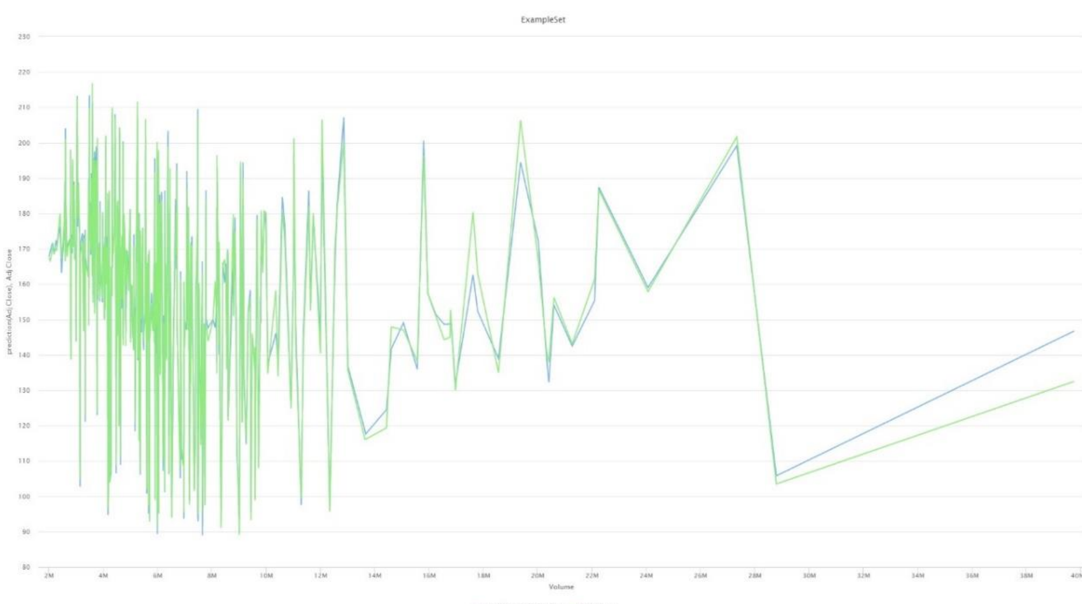
Absolute Error: 2.455 +/- 0.455 (micro average: 2.456 +/- 2.303)

Relative Error: 1.57% +/- 0.30% (micro average: 1.57% +/- 1.40%)

Prediction Average: 156.760 +/- 5.411 (micro average: 156.744 +/- 26.726)

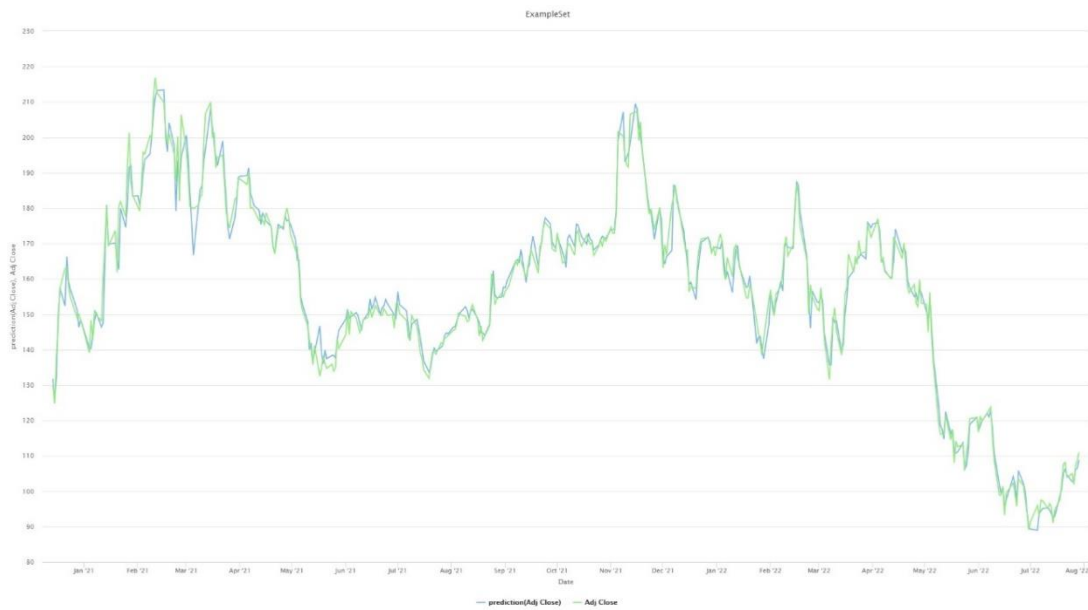
As can be seen above, the aggregate prediction average of the Adjusted Closing Price is almost equal to the actual level. Root Mean Squared Error is 3.293 +/-0.729, with a relative error of 1.57%+/-0.3. The predictive model applies to real-time, according to aggregate predictive estimation. Although the dependent variable (Adjusted Closing Price), which is the targeted attribute, exhibits pricing variations remarkably like those of the stock, the real adjusted closing price exhibits significant price changes, ranging from a low of 89.080 to a maximum of 216.840. Predictive data models that are based on the volume of shares and the date is below:

FIGURE 4.1: COMPARISON OF THE ADJUSTED CLOSING PRICE BASED ON THE VOLUME OF SHARES AND THE EXPECTED ADJUSTED CLOSING PRICE - AIRBNB



Based on the volume of shares, the model's predicted adjusted closing price outperforms the actual adjusted closing price, as shown.

FIGURE 4.2: COMPARISON OF THE ADJUSTED CLOSING PRICE BASED ON THE DATE AND THE EXPECTED ADJUSTED CLOSING PRICE – AIRBNB



The adjusted closing price predicted by the model outperforms the actual adjusted closing price, as demonstrated, based on the date of financial data.

4.1.2 Uber Data Analysis

Uber, intraday stock price data is between January 2, 2020, and July 29, 2022. The dependent variable adjusted close price and prediction is based on the aggregate factorization of other independent variables. Linear Regression Analysis is applied to the dataset under Cross Validation, and its performance indicators are measured. The independent variables are Open Price, High Price, Low Price, Close Price, and Volume of Shares. The table below is showing the actual and predicted prices of Adjusted Closing Price:

Table 4.2: Uber Linear Regression - Cross Validation Example Set

	Minimum Price	Maximum Price	Average

Adjusted Closing Price	14.820	63.180	39.382
Prediction (Adjusted Closing Price)	16.441	62.450	39.389
Open	15.960	63.250	39.435
High	17.800	64.050	40.263
Low	13.710	60.800	38.511
Close	14.820	63.180	39.382
Volume of Shares	6316800	115601800	27166977.504

The predicted adjusted closing price for Uber is comparable to the actual adjusted closing prices, as can be seen in the table above. Aggregate pricing is based on other independent variables (Open Price, High Price, Low Price, Date, and Volume of Shares). Performance metrics are shown below:

Performance Vector of Uber:

Root Mean Squared Error: 0.674 +/- 0.088 (micro average: 0.679 +/- 0.000)

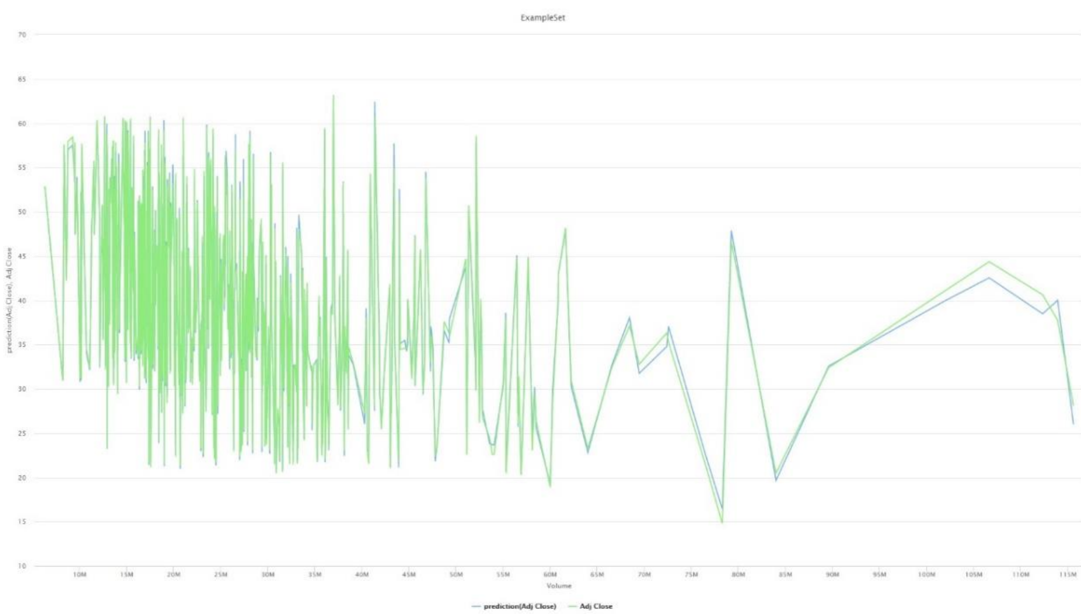
Absolute Error: 0.521 +/- 0.070 (micro average: 0.520 +/- 0.436)

Relative Error: 1.39% +/- 0.22% (micro average: 1.39% +/- 1.24%)

Prediction Average: 39.381 +/- 1.778 (micro average: 39.382 +/- 10.366)

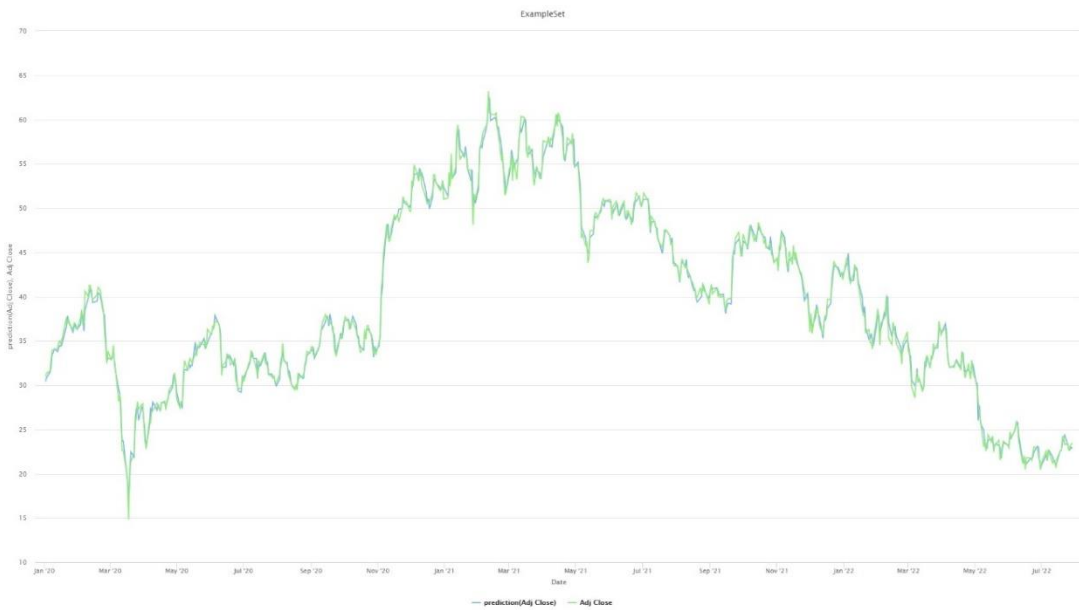
As can be seen above, the aggregate prediction average of the Adjusted Closing Price is almost equal to the actual level. Root Mean Squared Error is 0.674 +/-0.088, with a relative error of 1.39%+/-0.22. The predictive model applies to real-time, according to aggregate predictive estimation. In the Uber case, the real adjusted closing price shows a smaller price movement, ranging from a low of 14.820 to a maximum of 63.180, while the dependent variable (Adjusted Closing Price), which is the intended attribute, exhibits pricing variations strikingly comparable to those of the stock. Price variations in adjusted closing prices show a steadier movement. Predictive data models that are based on the volume of shares and the date is below:

FIGURE 4.3: COMPARISON OF THE ADJUSTED CLOSING PRICE BASED ON THE VOLUME OF SHARES AND THE EXPECTED ADJUSTED CLOSING PRICE - UBER



Based on the volume of shares, the model's predicted adjusted closing price outperforms the actual adjusted closing price, as shown.

FIGURE 4.4: COMPARISON OF THE ADJUSTED CLOSING PRICE BASED ON THE DATE AND THE EXPECTED ADJUSTED CLOSING PRICE - UBER



The adjusted closing price predicted by the model outperforms the actual adjusted closing price, as demonstrated, based on the date of financial data.

4.2 BIBLIOGRAPHIC COUPLING AND KEYWORD CO-OCCURRENCE ANALYSIS: STUDY OF KEYWORD ARRANGEMENTS

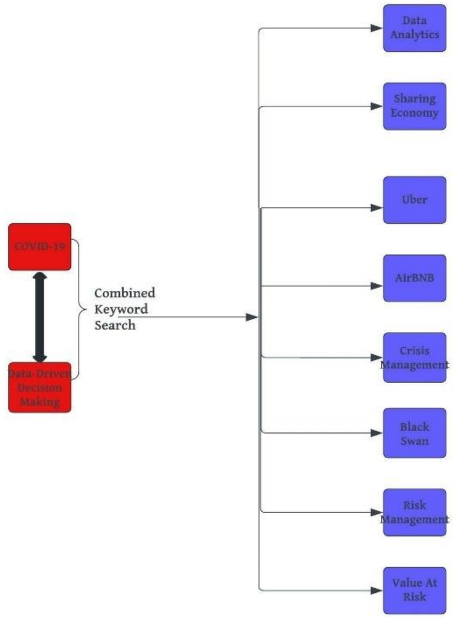
Articles were exported from the Web of Science Core Collection. The period of publication is between 2020 and 2022. Fractional counting and the unit of analysis as documents are selected. The minimum required citation count is three. The distance is used in Network Visualization to show how closely related journals are based on co-citations and bibliographic links (Van Eck and Waltman 2011). Visually speaking, the two journals are closer together the more closely they are related. A link is a relationship between two keywords that occur simultaneously, and overall link strength is the number of publications where two keywords cooccur (Van Eck and Waltman 2011). Stronger the link, the greater the degree of connection and relevance for the subjects.

The document search function on WoS is based on several arrangements of keyword combinations of the related keyword. This is based on the scenario analysis to observe the effects of the pandemic on the sharing economy and the manageability of data-driven decision-making for business operations. Diagrams of the data gathering flow model and the keyword arrangement chart were created using the Lucidchart visualization tool. Five different combinations are established, and each combination reflects different keyword orderings. With VOSViewer, all bibliometric calculations are performed. The tables are constructed to show the publications' highest-linked bibliographic links and keywords in terms of network visualization. The research subjects with the highest links, as shown by arbitrary numbers, may point to a research area that addresses the research objective or a significant factor or process that may influence the study questions. There are 15 entries on each table.

4.2.1 Case Study 1 of Keyword Configuration

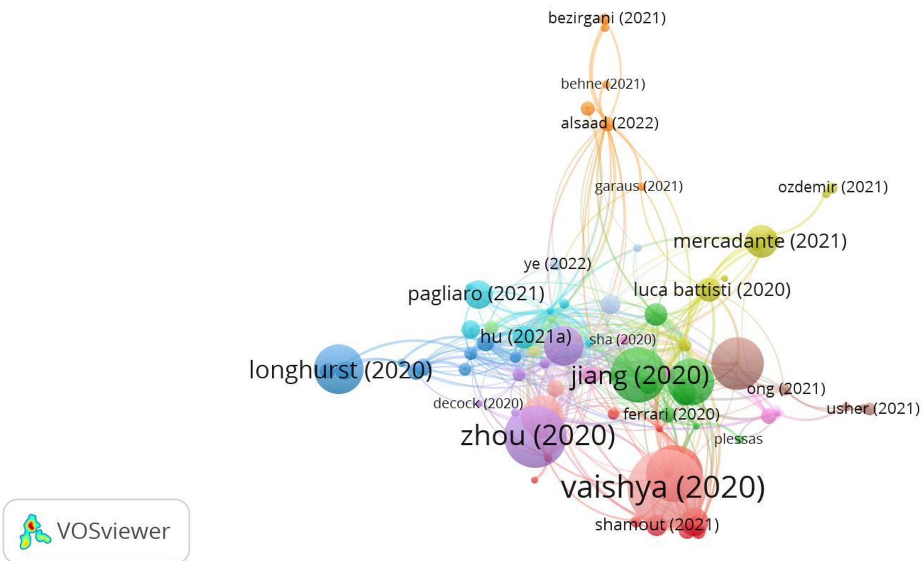
The first case study is based on the keyword search on the WoS database with several word orderings. The data chart model is below:

Figure 4.5: Keywords Configuration 1



As can be seen in the model above, other word combinations were searched along with COVID-19 and Data-Driven Decision Making. 208 articles were selected by VOSViewer software for bibliographic coupling. 108 documents meet the threshold with a minimum citation count of three, and the largest set of connected items is 85 documents. The bibliometric network visualization model is below:

FIGURE 4.6: KEYWORD CONFIGURATION 1 – BIBLIOGRAPHIC COUPLING NETWORK VISUALIZATION



There are several clusters in the network visualization of the keyword arrangement case study 1, as seen in the model above. The table below shows the publications' highest-linked keywords in terms of network visualization:

TABLE 4.3: HIGHEST LINKED ARTICLES WITH BIBLIOGRAPHIC COUPLED – KEYWORD CONFIGURATION 1

Authors	**Title of the Article**	**Publication Source, Volume (Issue Number): Page Number**	**Publication Year**	**Total Link Strength**	**The Purpose of the Study**

Teodoro Alamo, Daniel G. Reina, Pablo Millán Gata, Victor M. Preciado, Giulia Giordano	Data-driven methods for present and future pandemics: Monitoring, Modeling, and Managing	Annual Reviews in Control, Volume 52: 448-464	2021	40	Examining how data-driven techniques can be used for pandemic modeling and prevention.
Hayden Gunraj, Linda Wang, and Alexander Wong	COVIDNet-CT: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest CT Images	Frontiers in Medicine, Volume 7	2020	29	Establishing COVIDNet-CT Neural Network Architecture.
Hayden Gunraj, Ali Sabri, David Koff, and	COVID-Net CT-2: Enhanced	Frontiers in Medicine, Volume 8	2022	27	Enhanced deep neural networks are

Alexander Wong	Deep Neural Networks for Detection of COVID-19 From Chest CT Images Through Bigger, More Diverse Learning				presented for COVID-19 detection from chest CT images.
D. Ivanković, E. Barbazza, V. Bos, O. Brito Fernandes, K. Jamieson Gilmore, T. Jansen, P. Kara, N. Larrain, S. Lu, B. Meza-Torres, J. Mulyanto, M. Poldrugovac, A. Rotar, S. Wang,	Features Constituting Actionable COVID-19 Dashboards: Descriptive Assessment and Expert Appraisal of 158 Public Web-Based COVID-19 Dashboards	J. Med Internet Res, Volume 23(2): e25682	2021	23	Analyzing the functions and users of public COVID-19 dashboards to explore their qualities.

C. Willmington, Y. Yang, Z. Yelgezekova, S. Allin, N. Klazinga, and D. Kringos					
E. Barbazza, D. Ivanković, S. Wang, K. Gilmore, M. Poldrugovac, C. Willmington, N. Larrain, V. Bos, S. Allin, N. Klazinga, and D. Kringos	Exploring Changes to the Actionability of COVID-19 Dashboards Over the Course of 2020 in the Canadian Context: Descriptive Assessment and Expert Appraisal Study	Journal of Medical Internet Research, Volume 23(8)	2021	23	Exploring how COVID-19 dashboards evolved in the Canadian context during 2020.
Dimitris Bertsimas,	From Predictions to	Health Care Management	2021	22	Putting out a thorough data-

Leonard Boussioux, Ryan Cory-Wright, Arthur Delarue, Vassilis Digalakis, Alexandre Jacquillat, Driss Lahlou Kitane, Galit Lukin, Michael Li, Luca Mingardi, Omid Nohadani, Agni Orfanoudaki, Theodore Papalexopoulos, Ivan Paskov, Jean Pauphilet, Omar Skali Lami, Bartolomeo	Prescriptions: A Data-driven Response to COVID-19	Science, Volume 24(2): 253-272			driven strategy to comprehend the clinical traits of COVID-19, anticipate its evolution, and ultimately lessen its effects.

Stellato, Hamza Tazi Bouardi, Kimberly Villalobos Carballo, Holly Wiberg, and Cynthia Zeng					
Dario Esposito, Giovanni Dipierro, Alberico Sonnessa, Stefania Santoro, Simona Pascazio and Irene Pluchinotta	Data-Driven Epidemic Intelligence Strategies Based on Digital Proximity Tracing Technologies in the Fight against COVID-19 in Cities	Sustainability, Volume 13(2)	2021	21	Presenting and contrasting various Data-Driven Epidemic Intelligence techniques.
Ellen Kuhl	Data-Driven Modeling of COVID-19-	NPJ digital medicine, 4(1)	2020	17	Examining the use of data-driven

	Lessons Learned				modeling to combine traditional epidemiology models with machine learning to infer crucial disease parameters—in real-time—from reported case data to produce accurate predictions and direct public decision-making.
Annalise Riccardi, Jessica Gemignani,	Optimization of Non-pharmaceutical Measures in	IEEE Transactions on Emerging Topics in	2021	16	To predict daily coronavirus infections with

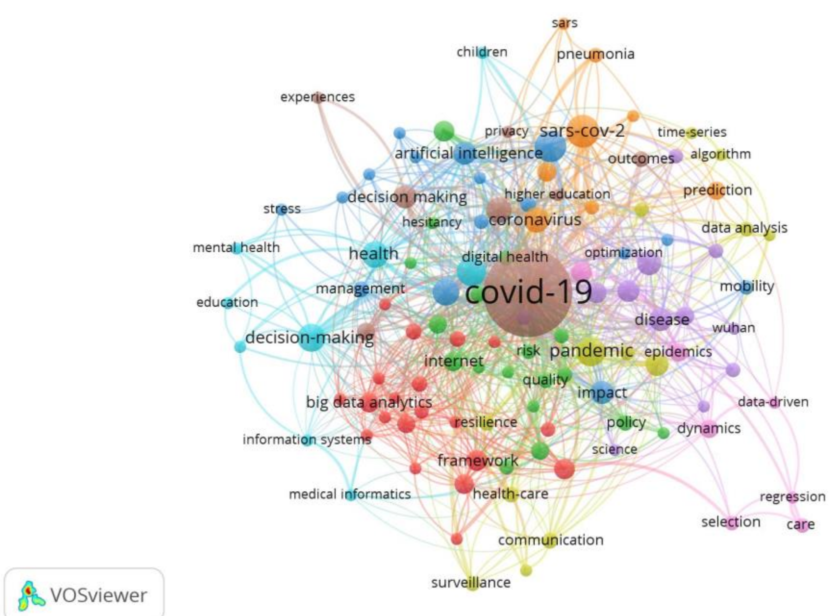
Fransisco Fernandez-navarro, Anna Heffernan	COVID-19 Growth via Neural Networks	Computational Intelligence, Volume: 5(1): 79-91			the use of a neural network model.
Mohamed Aziz Bhouri, Francisco Sahli Costabal, Hanwen Wang, Kevin Linka, Mathias Peirlinck, Ellen Kuhl, and Paris Perdikaris	COVID-19 dynamics across the US: A Deep Learning Study of Human Mobility and Social Behavior	Computer Methods in Applied Mechanics and Engineering, Volume 382	2021	13	Presenting a deep learning framework for identifying the epidemiology system.
Abdallah Alsaad, and Manaf Al-okaily	Acceptance of Protection Technology in a Time of Fear: The Case of COVID-19 Exposure Detection Apps	Information Technology and People, Volume 35(3): 1116-1135	2022	12	Investigating how protection technology is accepted in the context of the COVID-19 pandemic.

Sebastián Contreras, Juan Pablo Biron-Lattes, H. Andrés Villavicencio, David Medina-Ortiz, Nyna Llanovarced-Kawles, and Álvaro Olivera-Nappa	Statistically Based Methodology for Revealing Real Contagion Trends and Correcting Delay-induced Errors in the Assessment of the COVID-19 Pandemic	Chaos Solitons & Fractals, Volume 139	2020	12	Perform a temporal reclassification of cases to avoid delay-induced errors, by using a statistically based algorithm.
Damjan Manevski, Nina Ružić Gorenjec, Nataša Kejžar, and Rok Blagus	Modeling COVID-19 Pandemic Using Bayesian Analysis with Application to Slovene data	Mathematical Biosciences, Volume 329	2020	11	Proposing a semiparametric framework for modeling the COVID-19 pandemic.
Agnieszka Truszkowska,	High-Resolution	Advanced Theory and	2021	11	To simulate the spread of

Brandon Behring, Jalil Hasanyan, Lorenzo Zino, Sachit Butail, Emanuele Caroppo, Zhong-Ping Jiang, Alessandro Rizzo, and Maurizio Porfiri	Agent-Based Modeling of COVID-19 Spreading in a Small Town	Simulations, Volume 4(3)			COVID-19 in small towns and cities, an agent-based modeling framework is presented.
Duo Yu, Gen Zhu, Xueying Wang, Chenguang Zhang, Babak Soltanalizadeh, Xia Wang, Sanyi Tang, and Hulin Wu	Assessing Effects of Reopening Policies on COVID-19 Pandemic in Texas with a Data-driven Transmission Model	Infectious Disease Modelling, Volume 6: 461-473	2021	10	A novel SEIR model was developed to evaluate the effect of reopening policies based on the real-world reported COVID-19 data in Texas.

The bibliographic coupling with a stronger degree of connection presents data-driven methods and techniques that include response time and accurate predictions, a neural network for the detection of COVID-19 cases, a deep learning framework for identifying the epidemiology system, and a temporal classification model. Fractional Counting is selected for keyword count. 111 keywords meet the threshold of 1525 keywords with the minimum number of three keyword occurrences. The bibliometric network visualization model is below:

Figure 4.7: Keyword Occurrence for Keyword Configuration 1



As shown in the figure above, the COVID-19 keyword centered around policymaking, impact, healthcare, decision-making, education, and management-related words. Below are the top 15 instances of the chosen keyword:

TABLE 4.4: USING KEYWORD COMBINATIONS AND KEYWORD OCCURRENCES – SCENARIO 1

Keyword	**Occurrences**	**Total Link Strength**
COVID-19	140	127
SARS-CoV-2	19	18
Machine Learning	18	17
Big Data	16	16
Pandemic	16	15
Decision-Making	14	14
Coronavirus	12	12
Epidemiology	11	11
Health	13	11
Model	13	11
Artificial Intelligence	10	10
COVID-19 Pandemic	12	10
Decision Making	10	10
Disease	10	10

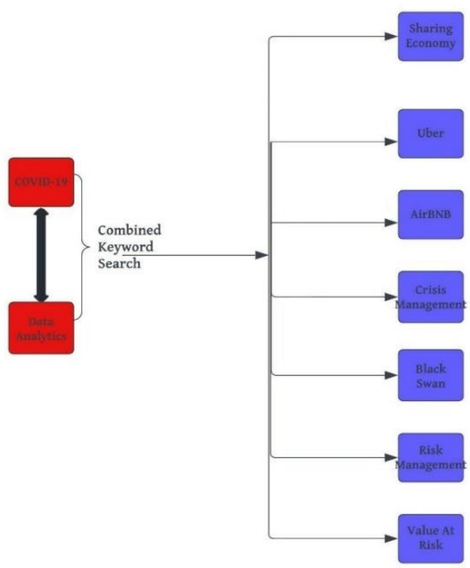
Impact	10	10

COVID-19 is circled big data, pandemic, decision-making, artificial intelligence, and disease as the most cited keywords.

4.2.2 CASE STUDY 2 OF KEYWORD CONFIGURATION

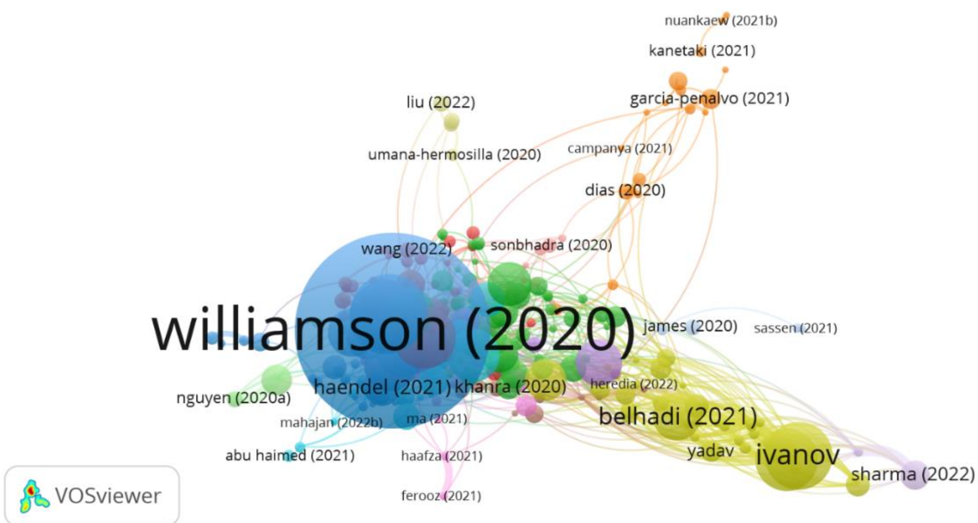
The second case study is based on the keyword search on the WoS database with several word orderings. The data chart model is below:

FIGURE 4.8: KEYWORD CONFIGURATION 2



As can be seen in the model above, other word combinations were searched along with COVID-19 and Data Analytics. Fractional counting is selected with a minimum of 3 citations. 384 documents meet the threshold out of 922 documents. The documents with the greatest total link strength are selected, where there are 364 documents. The bibliometric network visualization model is below:

FIGURE 4.9: KEYWORD CONFIGURATION 2 – BIBLIOGRAPHIC COUPLING NETWORK VISUALIZATION



The network visualization of the keyword arrangement case study 2 has several clusters, as seen in the model above. The table below shows the publications' highest-linked keywords in terms of network visualization:

TABLE 4.5: HIGHEST LINKED ARTICLES WITH BIBLIOGRAPHIC COUPLED – KEYWORD CONFIGURATION 2

Authors	**Title of the Article**	**Publication Source, Volume (Issue**	**Publication Year**	**Total Link Strength**	**The Purpose of the Study**

		Number): Page Number			
Dmitry Ivanov	Viable Supply Chain Model: Integrating Agility, Resilience, and Sustainability Perspectives —Lessons from and Thinking Beyond the COVID-19 Pandemic	Annals of Operation Research	2020	98	Introducing the flexible supply-demand allocation model, the Viable Supply Chain model.
Manish Mohan Baral, Rajesh Kumar Singh,	Analysis of Factors Impacting Survivability of Sustainable	The International Journal of Logistics Management	2021	84	The goal of the current study is to create a model for small and medium-sized businesses (SMEs') SUSSCs during the COVID-19 pandemic.

and Yiğit Kazançoğlu	Supply Chain during COVID-19 Pandemic: An Empirical Study in the Context of SMEs				Design/methodology/approach Constructs and items for gathering responses from various SMEs are identified with the aid of a thorough literature review.
Qiang Wang, Min Su, Min Zhang, and Rongrong Li	Integrating Digital Technologies and Public Health to Fight Covid-19 Pandemic: Key Technologies, Applications, Challenges and Outlook of Digital Healthcare	International Journal of Environmental Research and Public Health, Volume 18(11)		74	To assist us in containing the COVID-19 pandemic, this research undertook a systematic and thorough examination of digital healthcare. The background information and research overview of digital healthcare are covered in this essay. It then goes into some of the uses and difficulties it faced during the COVID-19 epidemic and concludes with some

					predictions about its future.
Manu Sharma, Icon, Sunil Luthra, Sudhanshu Joshi, and Anil Kumar	Developing a Framework for Enhancing the Survivability of Sustainable Supply Chains during and post-COVID-19 Pandemic	International Journal of Logistics-Research and Applications, Volume 25(4-5): 433-453	2022	74	Businesses are currently looking for strategies to improve the sustainability of their supply chains (SSCs). The goal of this project was to provide a framework for improving SSCs' ability to survive during and after the COVID-19 pandemic.
Alexander Spieske, and Hendrik Birkel	Improving Supply Chain Resilience Through Industry 4.0: A Systematic Literature Review	Computers & Industrial Engineering, Volume 158	2021	71	According to industry 4.0, there are promising ways to reduce supply chain risks like the COVID-19 pandemic. A thorough examination of the relationship between industry 4.0 and supply

	Under the Impressions of the COVID-19 Pandemic				chain resilience is however lacking in the literature. This research provides proof from a thorough literature evaluation to fill this study gap.
Dmitry Ivanov, and Alexandre Dolgui	A Digital Supply Chain Twin for Managing the Disruption Risks and Resilience in the Era of Industry 4.0	Production Planning & Control, Volume 32(9): 775-788	2021	71	In this study, the idea of a digital supply chain twin—a computerized model that depicts network states at any given instant in real time—is theorized. When controlling disruption risks in SCs, it examines the circumstances underlying the design and execution of digital twins.
Maciel M. Queiroz, Samuel Fosso	Supply Chain Resilience During the COVID-19:	Benchmarking -An International	2022	65	Despite the gains in the literature on supply chain resilience (SCR), there is still a significant gap in

Wamba, and Regina M. Branski	Empirical Evidence from an Emerging Economy	Journal, Volume 29(6)			our knowledge of SCR in high-disruption contexts, such as COVID-19. This study investigates the SCR's agility, resilience, disruption direction, and resource reconfiguration in the context of this extraordinary disruption in the Brazilian supply chain.
Cong T. Nguyen, Yuris Mulya Saputra, Nguyen Van Huynh, Ngoc-Tan Nguyen, Tran Viet Khoa, Bui	A Comprehensive Survey of Enabling and Emerging Technologies for Social Distancing—Part I: Fundamentals and	IEEE Access, Volume 8: 153479-153507	2020	63	To stop the transmission of viral diseases like COVID-19, social isolation is crucial. We can lower the likelihood that someone will contract the virus and disseminate it throughout the population by limiting close physical contact between individuals. This two-part essay tries to

Minh Tuan, Diep N. Nguyen, Dinh Thai Hoang, Thang X. Vu, Eryk Dutkiewicz, Symeon Chatzinotas, and Bjorn Otterson	Enabling Technologies				present a thorough assessment of how new technologies, such as wireless and networking, artificial intelligence (AI), and others, might permit, promote, and even impose the practice of social estrangement.
Maciel M. Queiroz, Samuel Fosso Wamba, Charbel Jose Chiappetta Jabbour,	Supply Chain Resilience in the UK during the Coronavirus Pandemic: A Resource Orchestration Perspective	International Journal of Production Economics, Volume 245	2022	60	Significant operations and supply chain interruptions were brought on by the COVID-19 outbreak. By putting out a novel model to investigate supply chain resilience (SCRE) antecedents and using supply chain alertness

and Marcio C. Machado					(SCAL) as a focal point to encourage resilience, this study seeks to fill this knowledge gap. To create a conceptual model, this work focuses on the resource orchestration theory (ROT).
Cong T. Nguyen, Yuris Mulya Saputra, Nguyen Van Huynh, Ngoc-Tan Nguyen, Tran Viet Khoa, Bui Minh Tuan, Diep N.	A Comprehensive Survey of Enabling and Emerging Technologies for Social Distancing—Part II: Emerging Technologies and Open Issues	IEEE Access, Volume 8: 154209-154236	2020	59	This two-part paper aims to provide a comprehensive survey on how emerging technologies, e.g., wireless, and networking, and artificial intelligence (AI) can enable, encourage, and even enforce social distancing practices. In Part, I, an extensive background of social distancing is provided, and enabling wireless technologies are

Nguyen, Dinh Thai Hoang, Thang X. Vu, Eryk Dutkiewicz, Symeon Chatzinotas, and Bjorn Otterson					thoroughly surveyed. In this Part II, emerging technologies such as machine learning, computer vision, thermal, ultrasound, etc., are introduced. These technologies open many new solutions and directions to deal with problems in social distancing, e.g., symptom prediction, detection, and monitoring of quarantined people, and contact tracing.
Q. -V. Pham, D. C. Nguyen, T. Huynh-The, W. -J. Hwang	Artificial Intelligence (AI) and Big Data for Coronavirus (COVID-19) Pandemic: A	IEEE Access, Volume 8: 130820-130839	2020	56.21	This research intends to highlight the significance of artificial intelligence (AI) and big data in responding to the COVID-19 outbreak and averting the devastating

and P. N. Pathirana	Survey on the State-of-the-Arts				impacts of the COVID-19 pandemic. It is motivated by recent developments and uses of AI and big data in many fields. The applications used to combat COVID-19 are then identified, obstacles and issues related to cutting-edge solutions are then highlighted, and lastly, recommendations are made for the communications to successfully control the COVID-19 scenario.
Mohd Javaid, Abid Haleem, Ravi Pratap Singh,	Significant Applications of Big Data in Industry 4.0	Journal of Industrial Integration and Management-Innovation and	2021	56	The key technologies used to successfully implement Industry 4.0 are big data, artificial intelligence (AI), robotics, the internet of things (IoT), cloud

and Rajiv Suman		Entrepreneurship, Volume 06(04): 429-447			computing, and 3D printing. The purpose of this study is to talk about the enormous potential of big data for Industry 4.0.
Rameshwar Dubey, David J. Bryde, Constantin Blome, David Roubaud, and Mihalis Giannakis	Facilitating Artificial Intelligence-Powered Supply Chain Analytics Through Alliance Management During the Pandemic Crises in the B2B Context	Industrial Marketing Management, Volume 96: 135-146	2021	52	Beyond anything that most people have experienced in their lifetime, the COVID-19 epidemic has disrupted international supply lines and exposed weak spots in the chains. This article examines alliance management capability (AMC) and artificial intelligence (AI) driven supply chain analytics capability (AI-SCAC) using the dynamic capabilities view, with environmental dynamism acting as a moderator.

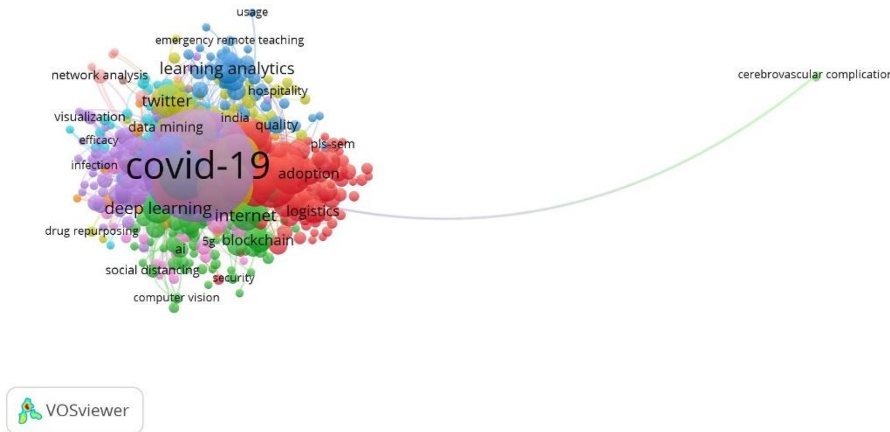
					Four study hypotheses are examined using survey information gathered from the Indian auto component manufacturing sector.
Sanjoy Kumar Paul, Priyabrata Chowdhury, Md. Abdul Moktadir, and Kwok Hung Lau	Supply Chain Recovery Challenges in the Wake of the COVID-19 Pandemic	Journal of Business Research, Volume 136: 316-329	2021	52	The COVID-19 pandemic has highlighted the vulnerability of global supply networks due to a lack of raw materials, disruptions in production and transportation, and social segregation. To preserve the sustainability of their companies and supply chains, firms must carefully foresee the challenges that may arise throughout the recovery period and develop appropriate plans. This study intends to identify

					and model recovery obstacles in the context of the Bangladeshi ready-made clothing sector to raise awareness of the problems. The data were analyzed using a DEMATEL (Delphi-based Grey Decision-Making Trial and Evaluation Laboratory) technique.
Farheen Naz, Anil Kumar, Abhijit Majumdar, and Rohit Agrawal	Is Artificial Intelligence an Enabler of Supply Chain Resiliency Post COVID-19? An Exploratory State-of-the-art Review	Operation Management Research	2021	48	There is an urgent need for supply chain resiliency because of the difficult circumstances and disruptions brought on by the COVID-19 epidemic (SCR). This study was carried out to determine the importance of artificial intelligence (AI) for developing a

	for Future Research				sustainable and resilient supply chain as well as to offer the best options for reducing supply chain risk. To analyze the prospective research contribution or directions in the areas of AI and SCR, a thorough literature study has been done.

As seen in the table above, an effective supply chain model has an impact on the chain's capacity to survive, while rising technologies (such as wireless networking...) and artificial intelligence support supply chain models that are driven by AI. Wireless networking and the Internet of Things made contact tracing possible. Fractional Counting is selected for keyword count. 453 keywords meet the threshold of 4007 keywords with the minimum number of three keyword occurrences. The bibliometric network visualization model is below:

FIGURE 4.10: KEYWORD OCCURRENCE FOR KEYWORD CONFIGURATION 2



As seen in the model above COVID-19 centered around data mining, twitter, deep learning, hospitality, visualization, and the internet. Below are the top 15 instances of the chosen keyword:

TABLE 4.6: USING KEYWORD COMBINATIONS AND KEYWORD OCCURRENCES – SCENARIO 2

Keyword	**Occurrences**	**Total Link Strength**
COVID-19	471	451
Big Data	119	119
Big Data Analytics	95	92
Data Analytics	91	91
Analytics	79	77
Machine Learning	78	77
Impact	77	75

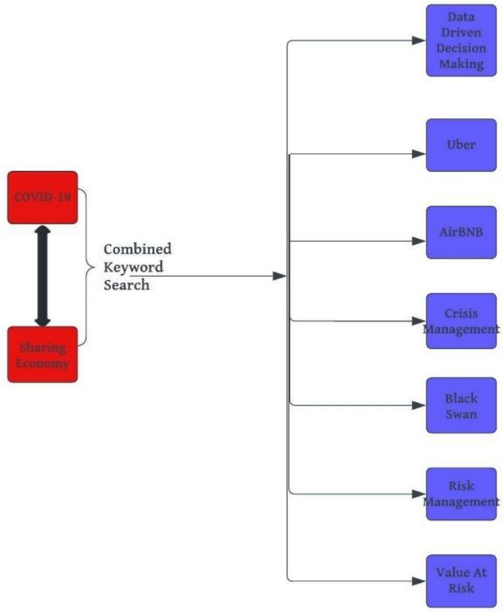
Artificial Intelligence	59	59
Management	57	57
Pandemic	57	56
Coronavirus	55	55
Performance	52	52
Social Media	54	52
Framework	51	51
SARS-CoV-2	45	43

The most often used terms in the coronavirus detection process, as seen in the table above, are management, framework, performance, artificial intelligence, social media, and the internet of things.

4.2.3 Case Study 3 of Keyword Configuration

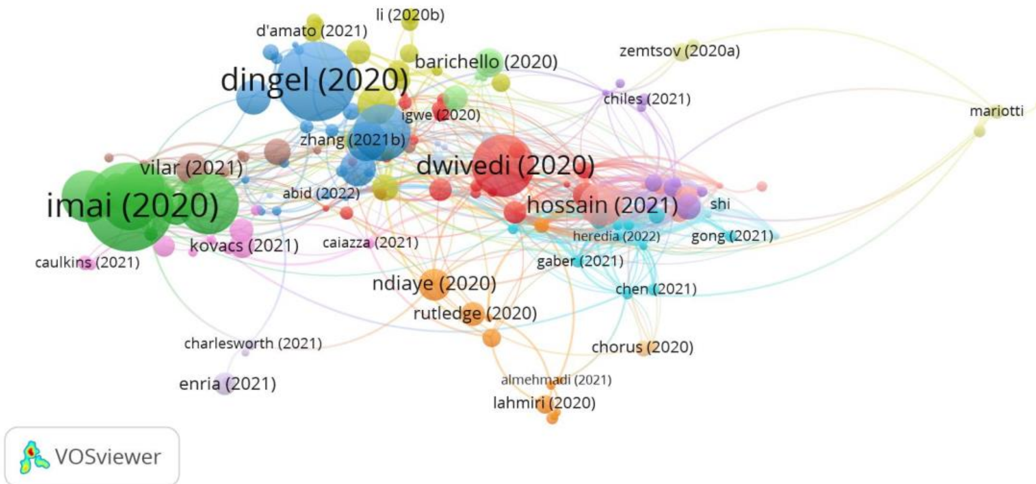
The third case study is based on the keyword search on the WoS database with several word orderings. The data chart model is below:

Figure 4.11: Keyword Configuration 3



As can be seen in the model above, other word combinations were searched along with COVID-19 and Sharing Economy. Fractional counting is selected with a minimum of 3 citations. 212 documents meet the threshold out of 548 documents. The documents with the greatest total link strength are selected, where there are 175 documents of the largest set of connected items. The model below is the bibliographic coupled network visualization:

FIGURE 4.12: KEYWORD CONFIGURATION 3 – BIBLIOGRAPHIC COUPLING NETWORK VISUALIZATION



The network visualization of the keyword arrangement case study 3 has several clusters, as seen in the model above. Below is the table highest linked article in the case study:

TABLE 4.7: HIGHEST LINKED ARTICLES WITH BIBLIOGRAPHIC COUPLED – KEYWORD CONFIGURATION 3

Authors	**Title of the Article**	**Publication Source, Volume (Issue Number): Page Number**	**Publication Year**	**Total Link Strength**	**The Purpose of the Study**

Meijian Yang, and Enjun Xia	A Systematic Literature Review on Pricing Strategies in the Sharing Economy	Sustainability, Volume 13 (17)	2021	58	The sharing economy is a new business model that has attracted a lot of academic interest. The price issue in the sharing economy has also been extensively researched. This study conducts a systematic literature review and content analysis of 158 articles from the Scopus and Web of Science databases to capture the most recent state-of-

					the-art research on pricing strategies in the sharing economy and identify future research possibilities.
Miao Mei, and Xu Tan	Current Strategies of Antiviral Drug Discovery for COVID-19	Frontiers in Molecular Biosciences, Volume 8	2021	48	SARS-CoV-2 was originally discovered in China in late 2019 and is a member of the family of enveloped, single-strand RNA viruses known as Betacoronavirus in the Coronaviridae. Antiviral medications

					targeting coronaviruses use a variety of approaches, including target-based drug development, large-scale phenotypic screening of chemical libraries, and empirical testing of well-established antiviral treatments. The current state of the COVID-19 drug discovery initiatives is discussed in this report, along

					with prospective future directions.
Zhihong Zuo, Ting Wu, Liangyu Pan, Chenzhe Zuo, Yingchuo Hu, Xuan Luo, Liping Jiang, Zanxian Xia, Xiaojuan Xiao, Jing Liu, Mao Ye, and Meichun Deng	Modalities and Mechanisms of Treatment for Coronavirus Disease 2019	Frontiers in Pharmacology, Volume 11	2021	47	The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes the 2019 coronavirus illness (COVID-19) is spreading quickly over the globe. Despite having a lower-case severity rate than SARS and the Middle East Respiratory Syndrome, COVID-19 is still a serious public worry due

					to its quick spread and catastrophic effects on the world economy. Anti-viral drugs and host system-modulating medicines might be considered the two main categories of current therapy. To better comprehend the mechanics of agents and provide an update on the state of the research, this document reviews the

					mechanisms of agents.
Ivana Načinović Braje, Anna Pechurina, Nilay Bıçakcıoğlu-Peynirci, Cristina Miguel, María del Mar Alonso-Almeida, and Carlo Giglio	The Changing Determinants of Tourists' Repurchase Intention: The Case of Short-Term Rentals During the COVID-19 Pandemic	International Journal of Contemporary Hospitality Management, Volume 34(1): 159-183	2022	45	The purpose of this research seeks to investigate repurchase intentions among short-term rental customers and variations in factors of repurchase intention in the context of the COVID-19 epidemic by using Ajzen's theory of planned behavior theoretical framework.

Stephanie Hui-Wen Chuaha, Raditia Yudistira Sujanto, Jovi Sulistiawan, and Eugene Cheng-Xi Aw	What is holding customers back? Assessing the Moderating Roles of Personal and Social Norms on CSR'S routes to Airbnb Repurchase Intention in the COVID-19 Era	journal of hospitality and tourism management, Volume 50: 67-82	2022	37	The COVID-19 pandemic has paralyzed peer-to-peer (P2P) accommodation markets despite Airbnb's devastation of the hotel sector. Airbnb increased its corporate social responsibility (CSR) efforts throughout the epidemic to rebuild confidence and create a compelling brand identity. The usefulness of CSR in

					promoting positive behavioral outcomes in emergencies is still up for debate. This research proposes a conceptual model to test the influence of Airbnb's CSR on repurchase/rebook intention through the mediation of customer trust and customer identification with the company, drawing on the

					theoretical lenses of stakeholder theory, norm activation model, and theory of planned behavior (C-C identification). The moderating effects of social and personal norms on the CSR-repurchase intention routes are also investigated in this study.
Xiaoxi Zhu, and Kai Liu	A Systematic Review and Future Directions of the Sharing Economy:	Journal of Cleaner Production, Volume 290	2021	37	With the introduction of several physical sharing platforms like Uber and

	Business Models, Operational Insights and Environment-based Utilities				Airbnb, the sharing economy (SE) business model is expanding quickly on a global scale. Existing research on the sharing economy focuses primarily on three key areas: the sharing economy's meaning, its business model, and its effects. This study begins by outlining the factors driving the sharing economy's

					growth and the reasons why users in a variety of occupations engage in it. The essential workings of the sharing economy's consumer-to-consumer (C2C) and business-to-consumer (B2C) elements are then briefly discussed. One of the primary drivers of the sharing economy is thought to be being eco-friendly.

Oksana Mont, Steven Kane Curtis, and Yuliya Voytenko Palgan	Organizational Response Strategies to COVID-19 in the Sharing Economy	Sustainable Production and Consumption, Volume 28: 52-70	2021	35	Global production and consumption habits have been altered by the COVID-19 epidemic, and numerous organizations have been obliged to react. However, it is unclear how the epidemic has affected sharing platforms, how they handled the crisis, and what sort of long-term effects the pandemic might have on the sharing

					economy. This study combined a thorough assessment of the literature with a qualitative web analysis of 30 platforms for sharing space, mobility, and products across various business models and geographical locations. Eight broad reaction tactics aimed toward the organization, users, and society make up an experimentally

					supported framework of organizational responses to COVID-19.
Makarand Amrish Mody, Lydia Hanks, and Mingming Cheng	Sharing Economy Research in Hospitality and Tourism: A Critical Review Using Bibliometric Analysis, Content Analysis, and a Quantitative Systematic Literature Review	International Journal of Contemporary Hospitality Management, Volume 33 (5): 1711-1745	2021	37	The goal of this study is to perform a critical evaluation of the literature on the sharing economy to pinpoint its primary intellectual underpinnings, trace their development, and make methodological and topic suggestions for further research

					that will progress the field.
Mokter Hossain	The Effect of the COVID-19 on Sharing Economy Activities	Journal of Cleaner Production, Volume 280	2021	31	The COVID-19 pandemic has endangered the sharing economy's (SE) operations. COVID-19 has prompted concerns about the SE's viability although it is perceived as a disruptive phenomenon, notably in the accommodation and transportation businesses. Understanding how the COVID-

					19 outbreak is affecting the SE sector is crucial. This study aims to investigate how COVID-19 affects sharing economy activity. The researchers used a range of media as data sources for this study, including news articles, TV news segments, YouTube videos, and blog postings.
Chia-Ying Li, and Mei-Chen Tsai	What Makes Guests Trust Airbnb? Consumer Trust	Journal of Hospitality and Tourism Management,	2022	29	The popularity of Airbnb as a platform for the sharing economy

	Formation and its Impact on Continuance Intention in the Sharing Economy	Volume 50: 44-54			has increased, and individuals' participation in the Airbnb sharing phenomena is driven by trust. Few researchers have thoroughly looked into the antecedents of these many forms of trust, even though studies have identified various forms of trust, such as confidence in the host and trust in the platform. This study experimentally

					investigated how customers acquire their trusting attitudes toward Airbnb using guest-based, host-based, and platform-based elements to show how important trust is to Airbnb. 416 participants provided data for this study, which was used to evaluate a structural model. The results demonstrated that levels of confidence in

					Airbnb were positively influenced by both the amount of trust among guests and the host-based components of information quality and media richness.
Eunsoo Baek, and Ga-eun (Grace) Oh	Diverse Values of Fashion Rental Service and Contamination Concerns of Consumers	Journal of Business Research, Volume 123: 165-175	2021	26	The fashion industry is paying more and more attention to fashion rental services as a kind of collaborative consumption. However, because of the COVID-19

					pandemic, firms who rent out clothing must carefully address customers' increased fears about contamination. To anticipate adoption intentions, this study tries to understand how various consumption values of the fashion rental service shape attitudes toward the service depending on one's contamination

					fears. To assess the data, structural equation modeling was employed. The results indicate that attitudes leading to adoption intentions are strongly increased by functional, economic, and emotional factors.
Oksana Gerwe	The COVID-19 Pandemic and the Accommodation Sharing Sector: Effects and	Technological Forecasting and Social Change, Volume 167	2021	24	One of the sectors that have been affected the worst is the hospitality business, which

	Prospects for Recovery				includes the sector of home-sharing. Under the new limitations, renting an Airbnb property, CouchSurfing, and transferring houses via LoveHomeSwap all become nearly impossible. This research paper examines how the Covid-19 crisis affected the rental housing market and theoretically identifies the underlying

					causes of its disruption. According to the analysis, the sector's key strength which had initially driven its growth—became its vulnerabilities because of the epidemic.
Kostas Mouratidis, Sebastian Peters, and Bert Van Wee	Transportation Technologies, Sharing Economy, and Teleactivities: Implications for Built Environment and Travel	Transportatio n Research Part D- Transport and Environment, Volume 92	2021	24	This essay examines the relationship between tele-activities, the sharing economy, and developing mobility technologies, which together

					make up what we can refer to as the "App City." And may have an impact on how people move and how cities are created. Findings imply that tele-activities may create certain trips while substituting for others. Telework and teleconferences could cut down on overall travel. According to research on the sharing economy,

					carsharing may reduce private car use and ownership, bike-sharing encourages more active travel and reduces car use, ride-sourcing ride-hailing) may increase vehicle miles traveled, while the effects of e-scooter sharing, ridesharing, and Mobility as a Service depend on the context.
Carla Maneira, Pamela Magalí	Exploring G Protein-coupled Receptors and Yeast Surface	Fems Yeast Research, Volume 21 (1)	2021	24	The impact of viral infections on healthcare systems and the

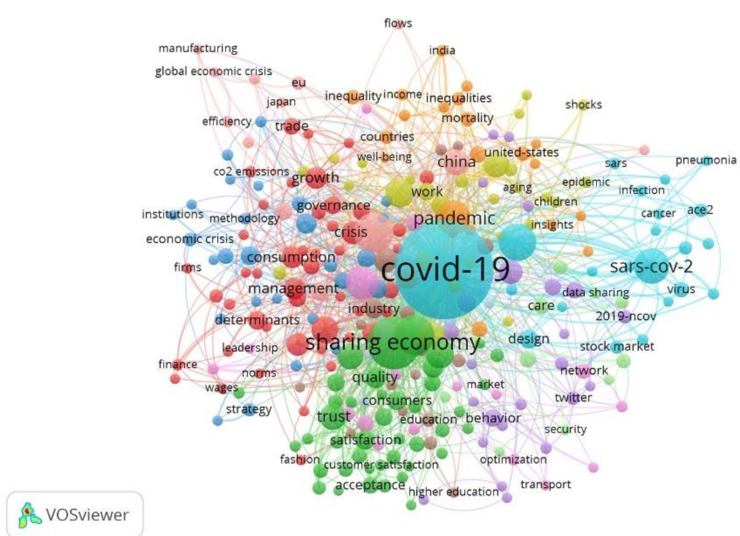
Bermejo, Gonçalo Amarante Guimarães Pereira, and Fellipe da Silveira Bezerra de Mello	Display Strategies for Viral Detection in Baker's yeast: SARS-CoV-2 as a Case Study				world economy is significant. An essential first step toward efficient therapies and management of viral infections is an accurate diagnosis. For several of the most significant viruses, biosensors have been effectively deployed as simple and reliable detection techniques. This study suggests a unique method for detecting viruses in

					Saccharomyces Cerevisiae that combines the G Protein-Coupled Receptors' (GPCRs') capacity for transduction with the Yeast Surface Display (YSD) of certain enzymes involved in viral recognition.
Stefano Bresciani, Alberto Ferraris, Gabriele Santoro, Katia Premazzi, Roberto	The Seven Lives of Airbnb. The Role of Accommodation Types	Annals of Tourism Research, Volume 88	2021	23	This study examines how COVID-19 is affecting various types of lodging and whether the demand for physical distance has an impact on

Quaglia, Dorra Yahiaoui, and Giampaolo Viglia,					travelers' lodging preferences.

The table above includes information on the business model for the sharing economy, current tactics and effective treatments for antiviral testing, evaluation of the social norms in hospitality, including organizational and friendly responses to COVID-19, consumer trust for continued intention to use the sharing economy, and research into the sharing economy's future. Fractional Counting is selected for keyword count. 277 keywords meet the threshold of 2894 keywords with the minimum number of three keyword occurrences. The bibliometric model is below:

FIGURE 4.13: KEYWORD OCCURRENCE FOR KEYWORD CONFIGURATION 3



The COVID-19 keyword is centered around manufacturing, growth, pandemic, infection, pneumonia, economic crisis, well-being, countries, efficiency, and carbon monoxide emissions, as shown in the figure above. Below are the top 15 instances of the chosen keywords:

TABLE 4.8: USING KEYWORD COMBINATIONS AND KEYWORD OCCURRENCES – SCENARIO 3

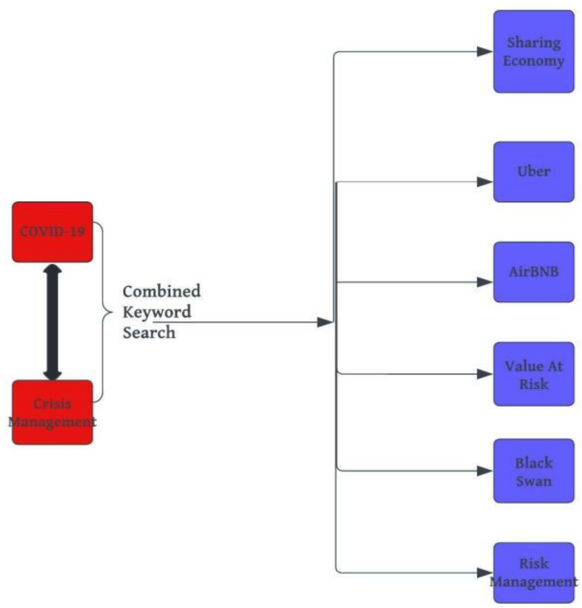
Keyword	Occurrences	Total Link Strength
COVID-19	260	230
Sharing Economy	75	74
Impact	42	40
Coronavirus	37	37
COVID-19 Pandemic	41	36
SARS-CoV-2	33	32
Pandemic	32	31
Sustainability	30	29
Economy	23	23
Airbnb	21	21
Performance	20	20
China	19	19
Trust	19	19
Health	19	18
Tourism	18	18

As seen the in the table above, pandemic, health tourism, performance, trust, sustainability, COVID-19 pandemic, and impact are the most cited keywords in the articles.

4.2.4 CASE STUDY 4 OF KEYWORD CONFIGURATION

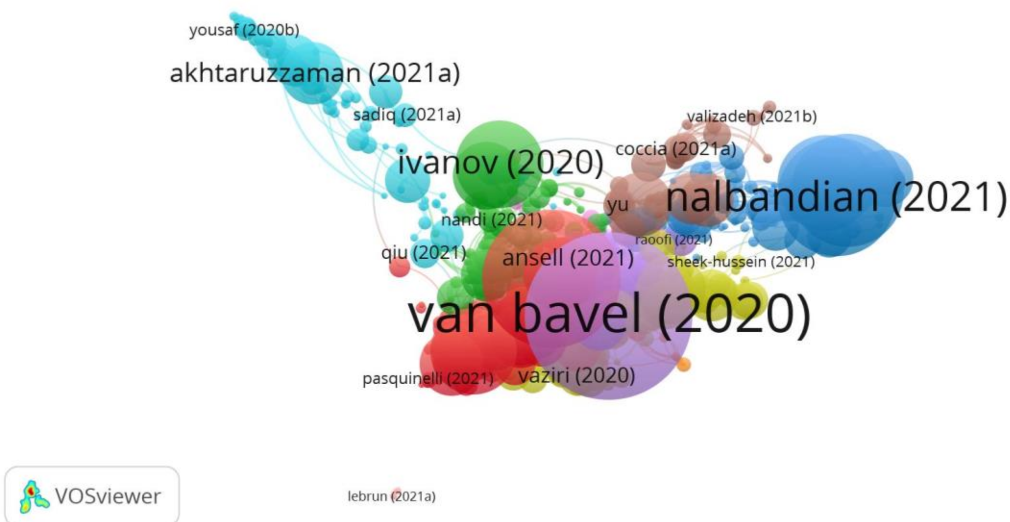
The fourth case study is based on the keyword search on the WoS database with several word orderings. The data chart model is below:

FIGURE 4.14: KEYWORD CONFIGURATION 4



As can be seen in the model above, other word combinations were searched along with COVID-19 and Crisis Management. Fractional counting is selected with a minimum of 3 citations. 3458 documents meet the threshold out of 7856 documents. The documents with the greatest total link strength are selected, where there are 1000 documents of the largest set of connected items. That's because of the VOSViewer software limitations for document selection. The model below is the bibliographic coupled network visualization of the selected articles:

FIGURE 4.15: KEYWORD CONFIGURATION 4 – BIBLIOGRAPHIC COUPLING NETWORK VISUALIZATION



The network visualization of the keyword arrangement case study 4 has several clusters, as seen in the model above. The table below is the highest linked articles in bibliographic coupled with their abstract:

TABLE 4.9: HIGHEST LINKED ARTICLES WITH BIBLIOGRAPHIC COUPLED – KEYWORD CONFIGURATION 4

Authors	Title of the Article	Publication Source, Volume (Issue Number): Page Number	Publication Year	Total Link Strength	The Purpose of the Study

Tai Ming Wut, Jing (Bill) Xu, and Shun-mun Wong	Crisis Management Research (1985-2020) in the Hospitality and Tourism Industry: A Review and Research Agenda	Tourism Management, Volume 85	2021	346	Due to COVID-19 (Coronavirus Disease 2019) in 2020, the world's tourism industry has already experienced a great deal of loss. Organizations in the hotel and tourism industries are increasingly interested in crisis management, including disaster management and risk management. This study

					attempts to look into pertinent research areas in the context of the hotel and tourism business.
C. Riggioni, P. Comberiati, M. Giovannini, I. Agache, M. Akdis, M. Alves-Correia, J. M. Antó, A. Arcolaci, A. K. Azkur, D. Azkur, B. Beken, C. Boccabella, J. Bousquet, H. Breiteneder, D. Carvalho, L. De Las Vecillas, Z. Diamant, I.	A Compendium Answering 150 Questions on COVID-19 and SARS-CoV-2	Allergy, Volume 75 (10): 2503-2541	2020	157	In China, the coronavirus illness was first identified in cases in December 2019. This condition has become a pandemic and is brought on by the severe acute respiratory syndrome-related coronavirus 2 (SARS-CoV-2). With a focus on the following

Eguiluz-Gracia, T. Eiwegger, S. Eyerich, W. Fokkens, Y.D. Gao, F. Hannachi, S. L. Johnston, M. Jutel, A. Karavelia, L. Klimek, B. Moya, K. C. Nadeau, R. O'Hehir, L. O'Mahony, O. Pfaar, M. Sanak, J. Schwarze, M. Sokolowska, M. J. Torres, W. van de Veen, M. C. van Zelm, D. Y. Wang, L. Zhang, R.					areas: virology, immunology, diagnosis, management of patients with allergic disease and asthma, treatment, clinical trials, drug discovery, vaccine development, and epidemiology, this paper responds to urgent questions posed by young clinicians and scientists on SARS-CoV-2, COVID-19, and allergy. Experts

Jiménez-Saiz, and C. A. Akdis					in the field responded to 150 questions in all, giving a thorough and useful review of COVID-19 and allergic illnesses.
Saad I Mallah, Omar K Ghorab, Sabrina Al-Salmi, Omar S Abdellatif, Tharmegan Tharmaratnam, Mina Amin Iskandar, Jessica Atef Nassef Sefen, Pardeep Sidhu, Bassam Atallah, Rania El-Lababidi, and	COVID-19: Breaking Down a Global Health Crisis	Annals of Clinical Microbiology and Antimicrobials, Volume 20 (1)	2021	150.78	Supportive care and anticoagulant treatments are included in patient management, with an emphasis on preserving respiratory function. Dexamethasone, Remdesivir, and Tocilizumab therapy currently

Manaf Al-Qahtani					seems to be the most effective option, with hydroxychloroquine, lopinavir, ritonavir, and interferons losing favor. Additionally, international immunization efforts have been stepped up, and many promising vaccinations have been widely used. Countries and stakeholders have implemented a variety of measures in response to the

					COVID-19 pandemic to stop the virus's spread, contain it, and lessen any negative side effects on the economy. The objective of this review study is to summarize the virus's effects on a global, micro to macro scale.
Zhenhuan Li, Dake Wang, Jaffar Abbas, Saad Hassan, Riaqa Mubeen	Tourists' Health Risk Threats Amid COVID-19 Era: Role of Technology Innovation, Transformati	Frontiers in Psychology, Volume 12	2022	144	During the COVID-19 pandemic epidemic, which severely affected travel and tourism around the world, technological

	on, and Recovery Implications for Sustainable Tourism				innovation changed the patterns of the travel and tourism business. The severe negative impacts of the coronavirus sickness led to a sharp drop in travel and tourism demand on a global scale. In the wake of the global crisis brought on by an infectious virus, this study concentrated on travel and tourism-related literature. To aid

					academics in better understanding the situation, the study seeks to critically analyze the recently published material. The virus COVID-19's opportunities for change and its effects on the travel and tourism sectors are valued. To promote sustainable development and recovery following the COVID-19

					pandemic, the study suggested a research methodology.
Sayeeda Rahman, Maria Teresa Villagomez Montero, Kherie Rowe, Rita Kirton, and Frank Kunik, Jr.	Epidemiology, Pathogenesis, Clinical Presentations, Diagnosis and Treatment of COVID-19: A Review of Current Evidence	Expert Review of Clinical Pharmacology, Volume 14 (5): 601-621	2021	136	An overview of the epidemiology, pathophysiology, clinical manifestation, diagnosis, and management of COVID-19 is provided in this publication. Those covered Coronavirus has been rapidly expanded via direct person-to-person respiratory transmission.

					The current clinical management of COVID-19 includes symptom management, infection prevention, and control measures, optimized supportive care, and intensive care support in severe or critical illnesses in the lack of any scientifically established treatment options. The creation of a

					potent vaccination is currently a top scientific focus.
Michela Piccarozzi, Cecilia Silvestri, and Patrizio Morganti	COVID-19 in Management Studies: A Systematic Literature Review	Sustainability, Volume 13 (7)	2021	121	The severe economic downturn that came after the pandemic's emergence has forced businesses and researchers to reevaluate the adjustments and fresh problems that are required to ensure their existence. The purpose of the study in this situation is to categorize and

					analyze the major contributions made on the COVID-19 topic in the managerial literature to identify gaps and points of view as well as potential future research directions.
Brent W. Ritchie, and Yawei Jiang	Risk, Crisis and Disaster Management in Hospitality and Tourism: A Comparative Review	International Journal of Contemporary Hospitality Management, Volume 33 (10): 3465-3493	2021	113	This paper seeks to provide an overview of the most recent findings on the subject of risk, crisis, and catastrophe management as well as in the tourism and

					hospitality industries. It identifies significant themes and contrasts the major subjects covered in the management and marketing literature for tourism and hospitality.
MD. Jamal Hossain, and S. M. Abdur Rahman	Repurposing Therapeutic Agents Against SARS-CoV-2 Infection: Most Promising and Neoteric Progress	Expert Review of Anti-Infective Therapy, Volume 19 (8): 1009-1027	2021	111	The SARS-CoV-2 etiological agent is highly contagious and poses a severe threat to the COVID-19 pandemic. The most successful repurposing

					therapy options have had their results updated (from January to August 2020) in this research paper to treat the SARS-CoV-2 viral illness.
Halie M. Rando, Nils Wellhausen, Soumita Ghosh, Alexandra J. Lee, Anna Ada Dattoli, Fengling Hu, James Brian Byrd, Diane N. Rafizadeh, Ronan Lordan, Yanjun Qi, Yuchen Sun,	Identification and Development of Therapeutics for COVID-19	mSystems, Volume 6 (6)	2021	101.3	The COVID-19 issue was quickly addressed by the scientific and medical communities, who also identified many potential treatments. The methods used to identify candidates can

Christian Brueffer, Jeffrey M. Field, Marouen Ben Guebila, Nafisa M. Jadavji, Ashwin N. Skelly, Bharath Ramsundar, Jinhui Wang, Rishi Raj Goel, YoSon Park, Simina M. Boca, Anthony Gitter, and Casey S. Greene					be divided into four main groups: data-driven identification (ID) of candidates based on physical properties or pharmacological compendia; adaptation of clinical approaches to diseases with related pathologies; adaptation based on virological properties; adaptation based on the host response. This

					research shows the capacity of interdisciplinary teamwork to quickly identify a virus and match its properties with existing or new medications, and it also offers significant insight into how the ongoing epidemic might be managed.
Jiancheng Zhang, Bing Xie, and Kenji Hashimoto	Current Status of Potential Therapeutic Candidates for the	Brain Behavior and Immunity, Volume 87: 59-73	2020	97	Treatment options for COVID-19 have been made more effective thanks to the lessons acquired from

	COVID-19 Crisis				managing respiratory viral infections in the past. Many prospective treatments, including palliative care, immunomodulatory drugs, antiviral therapy, and convalescent plasma transfusion, have been tried out in small clinical trials. This study paper introduces the mechanisms of action, safety, and efficacy of the current prospective

					therapeutic approaches for disorders linked to COVID-19 infection.
Utkarsh, and Marianna Sigala	A Bibliometric Review of Research on COVID-19 and Tourism: Reflections for Moving Forward	Tourism Management Perspectives, Volume 40	2021	96	This study uses a bibliometric analytic approach to comprehensively assess and retrospectively analyze the quickly growing body of literature on COVID-19 in the tourist and hospitality industries. A co-word analysis of 177 publications (published up through January

					2021) indicated that they were organized thematically around four main topics that addressed the following diverse issues: 1) The effects of COVID-19 on traveler choice, destination marketing, technology adoption, and visitors' well-being; 2) The future of tourism after COVID-19; 3) Managing Change in Tourism; and 4)

					The effects of COVID-19 on tourism and hospitality stakeholders. The results demonstrate that early articles are typically theoretical, descriptive, and premature.
Dmitry Ivanov	Viable Supply Chain Model: Integrating Agility, Resilience, and Sustainability Perspectives-	Annals of Operations Research	2020	95	A supply chain's (SC) viability refers to its capacity to sustain itself and endure in a changing environment by redesigning its structures and planning its

	Lessons from and Thinking Beyond the COVID-19 Pandemic				performance with long-term effects. This paper introduces a novel idea known as the viable supply chain (VSC). According to this method, viability is viewed as a fundamental SC quality encompassing agility, resilience, and sustainability. The VSC model's core concepts are flexible structural SC designs for

					supply-demand allocations and, most crucially, the construction and management of adaptive mechanisms for changes in structural designs.
Annett Lotzin, Linda Krause, Elena Acquarini, Dean Ajdukovic, Vittoria Ardino, Filip Arnberg, Maria Boettche, Maria Bragesjo, Malgorzata Dragan, Margarida Figueiredo-	Risk and Protective Factors, Stressors, and Symptoms of Adjustment Disorder during the COVID-19 pandemic – First Results of the	European Journal of Psychotraumatology, Volume 12 (1)	2021	94	People are exposed to a variety of stressors because of the COVID-19 pandemic, including quarantine, physical segregation, job loss, infection risk, and loved one loss. Such a

Braga, Odeta Gelezelyte, Piotr Grajewski, Xenia Anastassiou-Hadjicharalambous, Jana Darejan Javakishvili, Evaldas Kazlaukas, Lonneke Lenferink, Chrysanthi Lioupi, Brigitte Lueger-Schuster, Lela Tsiskarishvili, Trudy Mooren, Luisa Sales, Aleksandra Stevanovic,	ESTSS COVID-19 pan-European ADJUST Study				wide variety of stimuli have the potential to cause adjustment disorder symptoms. During the first year of the COVID-19 pandemic, this cross-sectional exploratory study looked at the connections between risk and protective factors, stresses, and adjustment disorder symptoms. The longitudinal ADJUST Study of the European

Irina Zrnic, and Ingo Schaefer					Society of Traumatic Stress Studies (ESTSS) was utilized to collect the data.
Chung-Shing Chan	Developing a Conceptual Model for the Post-COVID-19 Pandemic Changing Tourism Risk Perception	International Journal of Environmental Research and Public Health, Volume 18 (18)	2021	94	Destinations and travel markets need empirical research to support post-pandemic strategies, especially about the impact of changing perceptions on tourism risks, experiences, and behavioral intentions. This paper aims to propose a conceptual

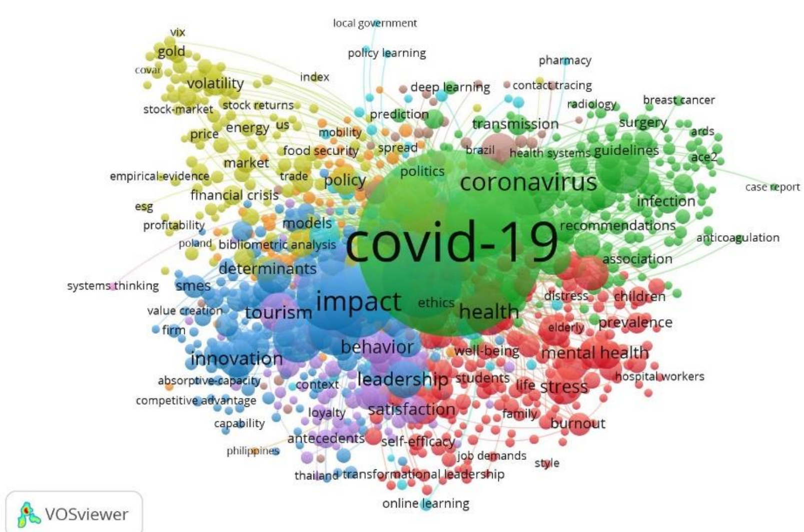
					model and its hypotheses of tourism risk from natural and man-made disasters and to explain the link between expected travel experience and final travel behavior.
Le Dang Lang, Abhishek Behl, Trung Dong Nguyen, Yama Temouri, and Hong Thu Nguyen	Effects of Social Capital on Agribusiness Diversification Intention in the Emerging Market	Journal of Intellectual Capital, Volume 23 (1): 56-84	2022	93	The 2019 novel coronavirus disease (COVID-19) has had a severe impact on the global economy. Using social capital to diversify agribusiness and attract more customers is a

					useful solution for agribusiness growth. Evidence on the impact of behavioral goals on aggregate social capital and intentions to diversify agribusiness is lacking. The purpose of this paper is to develop an integrative measure of social capital and to examine its effect on agribusiness diversification intentions using

					the Extended Theory of Planned Behavior (TPB).

The most connected topics, as shown in the table above, are flexible structural supply chain design for supply-demand allocations, investigation of agribusiness diversification and intentions, post-pandemic strategies for tourism experiences and behavioral intentions, patient management that includes prospective treatments, and crisis management in the tourism and hospitality industries. Fractional Counting is selected for keyword count. 2797 keywords meet the threshold of 18679 keywords with the minimum number of three keyword occurrences. The model below is the keywords network mapping:

FIGURE 4.16: KEYWORD OCCURRENCE FOR THE KEYWORD CONFIGURATION 4



As seen in the above image, the COVID-19 keyword is focused on effect, tourism, policy, systems thinking, politics, commerce, food security, stock returns, deep learning, health, spread, determinants, and some other phrases. Below are the top 15 instances of the chosen keyword:

TABLE 4.10: USING KEYWORD COMBINATIONS AND KEYWORD OCCURRENCES – SCENARIO 4

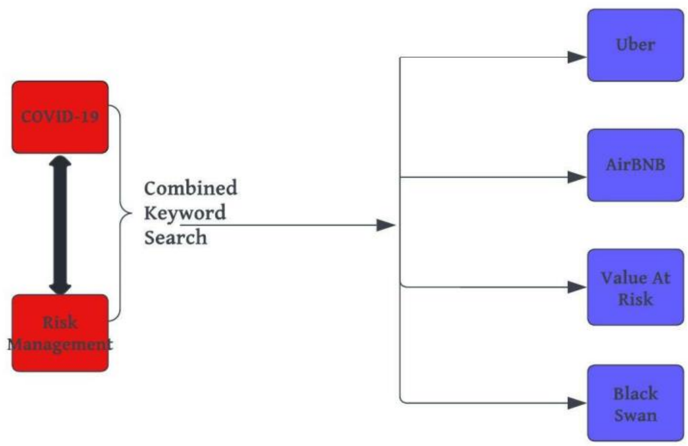
Keyword	Occurrences	Total Link Strength
COVID-19	4002	3789
Management	758	753
Pandemic	605	597
Impact	584	578
Crisis	563	560
Crisis Management	505	499
Coronavirus	481	474
COVID-19 Pandemic	374	344
SARS-CoV-2	342	336
Resilience	336	334
Performance	312	311
Risk	299	298
Health	263	256
Model	248	247
Communication	195	194

Management, pandemic, SARS-CoV-2 virus, risk, health, resilience, crisis management, model, and communication are the most often used keywords, as can be seen in the table above.

4.2.5 Case Study 5 of Keyword Configuration

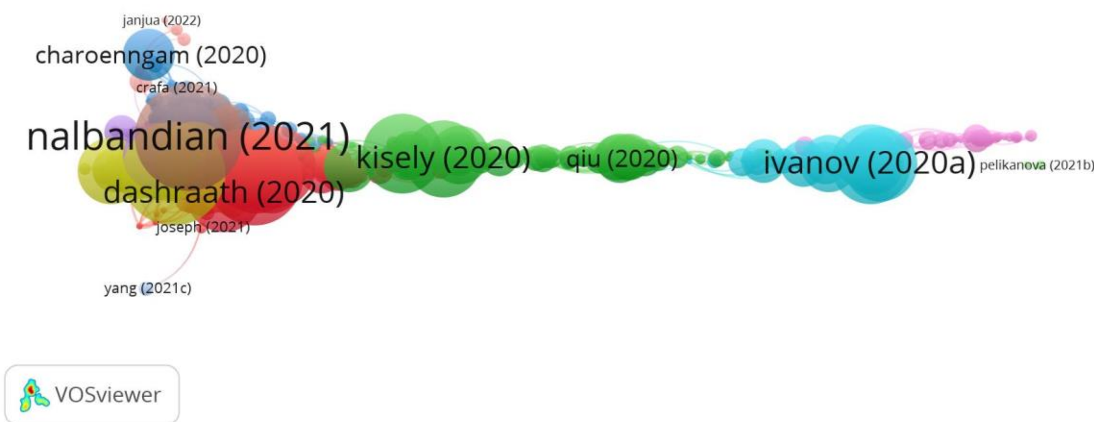
The fifth case study is based on the keyword search on the WoS database with several word orderings. The data chart model is below:

Figure 4.17: Keyword Configuration 5



As can be seen in the model above, other word combinations were searched along with COVID-19 and Risk Management. Some additional keyword arrangements were omitted to reduce repetition because they were often searched in the earlier word arrangement case studies. Fractional counting is selected with a minimum of 3 citations. 6567 documents meet the threshold out of 13901 documents. The documents with the greatest total link strength are selected, where there are 1000 documents of the largest set of connected items. That's because of the VOSViewer software limitations for document selection. Below is the network visualization model for the bibliographic coupling of selected articles:

Figure 4.18: Keyword Configuration 5 – Bibliographic Coupling Network Visualization



The network visualization of the keyword arrangement case study 5 has several clusters, as seen in the model above. The table below is the highest linked articles in bibliographic coupled with their abstract:

TABLE 4.11: HIGHEST LINKED ARTICLES WITH BIBLIOGRAPHIC COUPLED – KEYWORD CONFIGURATION 5

Authors	**Title of the Article**	**Publication Source, Volume (Issue Number): Page Number**	**Publication Year**	**Total Link Strength**	**The Purpose of the Study**
Colin Baigent, Stephan Windecker,	Esc Guidance for the Diagnosis and Management	Cardiovascular Research,	2022	297	The goal of this two-part research series is to provide

Daniele Andreini, Elena Arbelo, Emanuele Barbato, Antonio L Bartorelli, Andreas Baumbach, Elijah R Behr, Sergio Berti, Héctor Bueno, Davide Capodanno, Riccardo Cappato, Alaide Chieffo, Jean-Philippe Collet, Thomas Cuisset, Giovanni de Simone, Victoria	of Cardiovascular Disease During the COVID-19 Pandemic: Part 2-Care Pathways, Treatment, and Follow-up	Volume 118 (7): 1618-1666			practical knowledge and guidance to help clinicians diagnose and treat cardiovascular disease (CV) associated with COVID-19.

Delgado, Paul Dendale, Dariusz Dudek, Thor Edvardsen, Arif Elvan, José R. González- Juanatey, Mauro Gori, Diederick Grobbee, Tomasz J. Guzik, Sigrun Halvorsen, Michael Haude, Hein Heidbuchel, Gerhard Hindricks, Borja Ibanez, Nicole Karam, Hugo Katus,					

Fredrikus A. Klok, Stavros V. Konstantinides, Ulf Landmesser, Christophe Leclercq, Sergio Leonardi, Maddalena Lettino, Giancarlo Marenzi, Josepa Mauri, Marco Metra, Nuccia Morici, Christian Mueller, Anna Sonia Petronio, Marija M Polovina, Tatjana					

Potpara, Fabien Praz, Bernard Prendergast, Eva Prescott, Susanna Price, Piotr Pruszczyk, Oriol Rodríguez-Leor, Marco Roffi, Rafael Romaguera, Stephan Rosenkranz, Andrea Sarkozy, Martijn Scherrenberg, Petar Seferovic, Michele Senni, Francesco R. Spera, Giulio					

Stefanini, Holger Thiele, Daniela Tomasoni, Lucia Torracca, Rhian M. Touyz, Arthur A. Wilde, and Bryan Williams					
Colin Baigent, Stephan Windecker, Daniele Andreini, Elena Arbelo, Emanuele Barbato, Antonio L Bartorelli, Andreas Baumbach, Elijah R Behr,	Esc Guidance for the Diagnosis and Management of Cardiovascular Disease During the COVID-19 pandemic: Part 2-Care pathways, Treatment, and Follow-up	European Heart Journal, Volume 43 (11): 1059-1103	2022	292	The goal of this two-part series of studies is to provide practical knowledge and guidance to assist clinicians in the diagnosis and management of cardiovascular disease (CV) associated with COVID-19.

Sergio Berti, Héctor Bueno, Davide Capodanno, Riccardo Cappato, Alaide Chieffo, Jean-Philippe Collet, Thomas Cuisset, Giovanni de Simone, Victoria Delgado, Paul Dendale, Dariusz Dudek, Thor Edvardsen, Arif Elvan, José R. González-Juanatey, Mauro Gori,					

Diederick Grobbee, Tomasz J. Guzik, Sigrun Halvorsen, Michael Haude, Hein Heidbuchel, Gerhard Hindricks, Borja Ibanez, Nicole Karam, Hugo Katus, Fredrikus A Klok, Stavros V. Konstantinides, Ulf Landmesser, Christophe Leclercq, Sergio Leonardi,					

Maddalena Lettino, Giancarlo Marenzi, Josepa Mauri, Marco Metra, Nuccia Morici, Christian Mueller, Anna Sonia Petronio, Marija M. Polovina, Tatjana Potpara, Fabien Praz, Bernard Prendergast, Eva Prescott, Susanna Price, Piotr Pruszczyk, Oriol Rodríguez-Leor, Marco					

Roffi, Rafael Romaguera, Stephan Rosenkranz, Andrea Sarkozy, Martijn Scherrenberg, Petar Seferovic, Michele Senni, Francesco R. Spera, Giulio Stefanini, Holger Thiele, Daniela Tomasoni, Lucia Torracca, Rhian M Touyz, Arthur A Wilde, and Bryan Williams					

Tai Ming Wut, Jing (Bill) Xu, and Shun-mun Wong	Crisis Management Research (1985? 2020) in the Hospitality and Tourism Industry: A Review and Research Agenda	Tourism Management, Volume 85	2021	252	Crisis management, including disaster management and risk management, has become an important topic for organizations in the hospitality and tourism industry. The purpose of this study is to examine relevant research areas in the context of the hotel and tourism industry. The authors reviewed articles related to COVID-19, and the hospitality and tourism industry.

Colin Baigent, Stephan Windecker, Daniele Andreini, Elena Arbelo, Emanuele Barbato, Antonio L. Bartorelli, Andreas Baumbach, Elijah R Behr, Sergio Berti, Héctor Bueno, Davide Capodanno, Riccardo Cappato, Alaide Chieffo, Jean-Philippe Collet, Thomas Cuisset,	European Society of Cardiology Guidance for the Diagnosis and Management of Cardiovascular Disease During the COVID-19 Pandemic: Part 1-Epidemiology, Pathophysiology, and Diagnosis	European Heart Journal, Volume 43 (11): 1033-1058	2022	215	The goal of this two-part research series is to provide practical knowledge and guidance to help clinicians diagnose and treat cardiovascular disease (CVD) associated with COVID-19.

Giovanni de Simone, Victoria Delgado, Paul Dendale, Dariusz Dudek, Thor Edvardsen, Arif Elvan, José R. González-Juanatey, Mauro Gori, Diederick Grobbee, Tomasz J. Guzik, Sigrun Halvorsen, Michael Haude, Hein Heidbuchel, Gerhard Hindricks,					

Borja Ibanez, Nicole Karam, Hugo Katus, Fredrikus A. Klok, Stavros V. Konstantinides, Ulf Landmesser, Christophe Leclercq, Sergio Leonardi, Maddalena Lettino, Giancarlo Marenzi, Josepa Mauri, Marco Metra, Nuccia Morici, Christian Mueller, Anna Sonia Petronio,					

Marija M Polovina, Tatjana Potpara, Fabien Praz, Bernard Prendergast, Eva Prescott, Susanna Price, Piotr Pruszczyk, Oriol Rodríguez-Leor, Marco Roffi, Rafael Romaguera, Stephan Rosenkranz, Andrea Sarkozy, Martijn Scherrenberg, Petar Seferovic,					

Michele Senni, Francesco R Spera, Giulio Stefanini, Holger Thiele, Daniela Tomasoni, Luccia Torracca, Rhian M. Touyz, Arthur A. Wilde, and Bryan Williams					
Colin Baigent, Stephan Windecker, Daniele Andreini, Elena Arbelo, Emanuele Barbato, Antonio L.	European Society of Cardiology Guidance for the Diagnosis and Management of Cardiovascular Disease During the COVID-19	Cardiovascular Research, Volume 118 (6): 1385-1412	2022	215	The goal of this two-part research series is to provide practical knowledge and guidance to help clinicians diagnose and treat cardiovascular

Bartorelli, Andreas Baumbach, Elijah R Behr, Sergio Berti, Héctor Bueno, Davide Capodanno, Riccardo Cappato, Alaide Chieffo, Jean-Philippe Collet, Thomas Cuisset, Giovanni de Simone, Victoria Delgado, Paul Dendale, Dariusz Dudek, Thor Edvardsen, Arif Elvan,	Pandemic: Part 1-Epidemiology, Pathophysiology, and Diagnosis				disease (CVD) associated with COVID-19.

José R González-Juanatey, Mauro Gori, Diederick Grobbee, Tomasz J. Guzik, Sigrun Halvorsen, Michael Haude, Hein Heidbuchel, Gerhard Hindricks, Borja Ibanez, Nicole Karam, Hugo Katus, Fredrikus A. Klok, Stavros V. Konstantinides, Ulf Landmesser,					

Christophe Leclercq, Sergio Leonardi, Maddalena Lettino, Giancarlo Marenzi, Josepa Mauri, Marco Metra, Nuccia Morici, Christian Mueller, Anna Sonia Petronio, Marija M. Polovina, Tatjana Potpara, Fabien Praz, Bernard Prendergast, Eva Prescott, Susanna Price, Piotr					

Pruszczyk, Oriol Rodríguez-Leor, Marco Roffi, Rafael Romaguera, Stephan Rosenkranz, Andrea Sarkozy, Martijn Scherrenberg, Petar Seferovic, Michele Senni, Francesco R. Spera, Giulio Stefanini, Holger Thiele, Daniela Tomasoni, Luccia Torracca,					

Rhian M Touyz, Arthur A. Wilde, and Bryan Williams					
Matteo Bassetti, Daniele Roberto Giacobbe, Paolo Bruzzi, Emanuela Barisione, Stefano Centanni, Nadia Castaldo, Silvia Corcione, Francesco Giuseppe De Rosa, Fabiano Di Marco, Andrea Gori,	Clinical Management of Adult Patients with COVID-19 Outside Intensive Care Units: Guidelines from the Italian Society of Anti-Infective Therapy (sita) and the Italian Society of Pulmonology (sip)	Infectious Diseases and Therapy, Volume 10 (4): 1837-1885	2021	183	The Italian Society of Anti-Infective Therapy (SITA) and the Italian Society of Pulmonology (SIP) formed an expert panel to develop evidence-based guidelines for the clinical management of adult patients with coronavirus disease 2019 (COVID-19) outside the

Andrea Gramegna, Guido Granata, Angelo Gratarola, Alberto Enrico Maraolo, Malgorzata Mikulska, Andrea Lombardi, Federico Pea, Nicola Petrosillo, Dejan Radovanovic, Pierachille Santus, Alessio Signori, Emanuela Sozio, Elena Tagliabue, Carlo Tascini,					intensive care units.

Carlo Vancheri, Antonio Vena, Pierluigi Viale, and Francesco Blasi					
Saad I. Mallah, Omar K Ghorab, Sabrina Al-Salmi, Omar S Abdellatif, Tharmegan Tharmaratnam, Mina Amin Iskandar, Jessica Atef Nassef Sefen, Pardeep Sidhu, Bassam Atallah, Rania El-Lababidi,	COVID-19: Breaking Down a Global Health Crisis	Annals of Clinical Microbiology and Antimicrobials, Volume 20 (1)	2021	178.8	In response to the COVID-19 pandemic, countries are taking various precautionary measures to combat the virus, contain its spread, and mitigate economic collateral damage. This review paper aims to integrate global viral impacts from

and Manaf Al-Qahtani					macro to micro scales.
Chris R. Triggle, Devendra Bansal, Hong Ding, MD. Mazharul Islam, Elmoubashar Abu Baker Abd Farag, Hamad Abdel Hadi, and Ali A. Sultan	A Comprehensive Review of Viral Characteristics, Transmission, Pathophysiology, Immune Response, and Management of SARS-CoV-2 and COVID-19 as a Basis for Controlling the Pandemic	Frontiers in Immunology, Volume 12	2021	172	The SARS-CoV-2 coronavirus was identified as the causative agent, and its spread has strained the capacity of healthcare systems and adversely affected the global economy. This study and review provide the latest information on the virus, including its genome, risks associated with the emergence of variants, routes of transmission, immune

					responses, COVID-19 in children and the elderly, and advances in disease containment, prevention, and management. provide.
Sayeeda Rahman, Maria Teresa Villagomez Montero, Kherie Rowe, Rita Kirton, and Frank Kunik Jr.	Epidemiology, Pathogenesis, Clinical Presentations, Diagnosis and Treatment of COVID-19: A Review of Current Evidence	Expert Review of Clinical Pharmacology, Volume 14 (5): 601-621	2021	172	This study provides an overview of the epidemiology, pathogenesis, clinical presentation, diagnosis, and treatment of COVID-19.
Giuseppe Lisco, Anna De	COVID-19 and the Endocrine	Journal of Clinical	2021	167	This study summarizes

Tullio, Assunta Stragapede, Antonio Giovanni Solimando, Federica Albanese, Martina Capobianco, Vito Angelo Giagulli, Edoardo Guastamacchia, Giovanni De Pergola, Angelo Vacca, Vito Racanelli, and Vincenzo Triggiani	System: A Comprehensive Review on the Theme	Medicine, Volume 10 (3)			endocrine diseases and coronavirus disease 2019 (COVID-19).
Soo Lim, Jae Hyun Bae, Hyuk-Sang	COVID-19 and Diabetes Mellitus: From	Nature Reviews Endocrinology,	2021	165	Early studies found increased severity of

Kwon, and Michael A. Nauck	Pathophysiology to Clinical Management	Volume 17 (1): 11-30			coronavirus disease 2019 (COVID-19) caused by infection with severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in diabetic patients. Most of the available evidence does not distinguish between the main types of diabetes and is associated with type 2 diabetes due to its high prevalence. However, there is now some limited

					evidence regarding type 1 diabetes and COVID-19. This study reviews the conclusions and optimal management of patients with diabetes mellitus.
Ani Nalbandian, Kartik Sehgal, Aakriti Gupta, Mahesh V. Madhavan, Claire McGroder, Jacob S. Stevens, Joshua R. Cook, Anna S. Nordvig, Daniel Shalev,	Post-Acute COVID-19 Syndrome	Nature Medicine. Volume 27 (4): 601-615	2021	164	As the number of patients recovering from COVID-19 increases, COVID-19 is recognized as a multisystem disease with a wide range of symptoms. Like post-acute viral syndromes

Tejasav S. Sehrawat, Neha Ahluwalia, Behnood Bikdeli, Donald Dietz, Caroline Der-Nigoghossian, Nadia Liyanage-Don, Gregg F. Rosner, Elana J. Bernstein, Sumit Mohan, Akinpelumi A. Beckley, David S. Seres, Toni K. Choueiri, Nir Uriel, John C. Ausiello, Domenico Accili, Daniel E. Freedberg,					described in survivors of other virulent coronavirus epidemics, there are increasing reports of persistent and persistent effects following acute COVID-19. This study discusses considerations related to the multidisciplinary care of survivors and provides a framework for identifying individuals at increased risk of post-acute COVID-19 and

Matthew Baldwin, Allan Schwartz, Daniel Brodie, Christine Kim Garcia, Mitchell S. V. Elkind, Jean M. Connors, John P. Bilezikian, Donald W. Landry, and Elaine Y. Wan					their coordinated management through dedicated COVID-19 clinics.
Shatha K. Alyammahi, Shifaa M. Abdin, Dima W. Alhamad, Sara M. Elgendy, Amani T. Altell, and	The Dynamic Association Between COVID-19 and Chronic Disorders: An Updated Insight into Prevalence, Mechanisms,	Infection Genetics and Evolution, Volume 87	2021	162	A growing body of data suggests that COVID-19 disease develops in severe forms in patients who already have chronic conditions such as cardiovascular

Hanya A. Omar	and Therapeutic Modalities				disease, diabetes, respiratory disease, and kidney disease. This means that these patients are more susceptible to the disease and have a higher mortality rate. The study discusses treatment plans for specific patient populations, to minimize complications and achieve the best possible outcome.
Amy H. Attaway, Rachel G. Scheraga, Adarsh	Severe COVID-19 Pneumonia: Pathogenesis and Clinical Management	British Medical Journal, Volume 372	2021	161	The ongoing coronavirus disease (Covid-19) outbreak of 2019 has posed

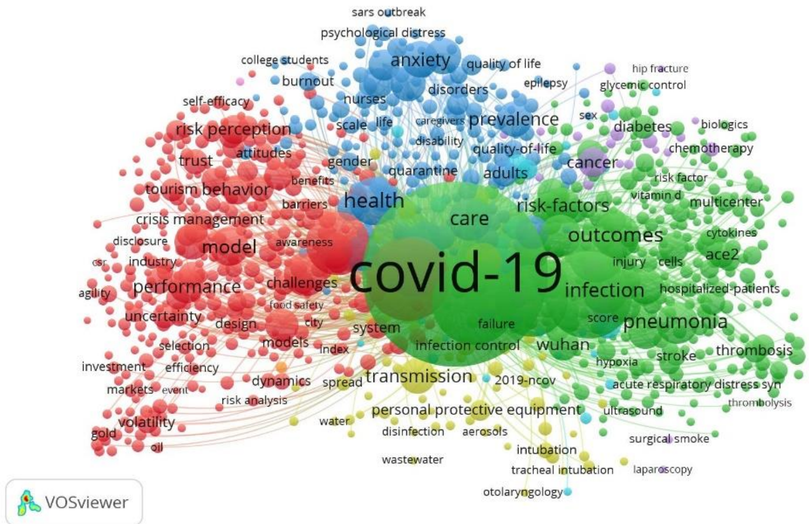
Bhimraj, Michelle Biehl, and Umur Hatipoglu					immense challenges to research and healthcare. Older age, male sex, and comorbidities increase the risk of serious illness. This review focuses on the epidemiological and clinical features of Covid-19, pathophysiological mechanisms, respiratory support in hospitalized patients, and the evidence to date on pharmacological treatment.

Ariel Izcovich, Martín Alberto Ragusa, Fernando Tortosa, María Andrea Lavena Marzio, Camila Agnoletti, Agustín Bengolea, Agustina Ceirano, Federico Espinosa, Ezequiel Saavedra, Verónica Sanguine, Alfredo Tassara, Candelaria Cid, Hugo Norberto Catalano,	Prognostic Factor for Severity and Mortality in Patients Infected with COVID-19: A Systematic Review	PLOS One, Volume 15 (1)	2020	158	The goal of our systematic review is to identify prognostic factors that can be used in decision-making related to the care of patients infected with COVID-19.

Arnav Agarwal, Farid Foroutan, and Gabriel Rada					

Most of the topics that are connected are, as can be seen in the table above, the clinical diagnosis and treatment of COVID-19, management of cardiovascular disease (CVD) associated with coronavirus, treatment of severe coronavirus illness in chronically ill persons (such as cardiovascular disease, diabetes, respiratory disease, and kidney disease...), formation of an expert panel to develop evidence-based guidelines for the clinical management of adult patients with coronavirus disease, and preventative measures to fight the virus. Fractional Counting is selected for keyword count. 5486 keywords meet the threshold of 32449 keywords with the minimum number of three keyword occurrences. Below is the network mapping of the most cited keywords:

FIGURE 4.19: KEYWORD OCCURRENCE FOR KEYWORD CONFIGURATION 5



The COVID-19 keyword is centered on performance, crisis management, challenges, risk perception, tourism behavior, design, investment, health, outcomes, prevalence, pneumonia, anxiety, and some other words. Below are the top 15 instances of the chosen keyword:

TABLE 4.12: USING KEYWORD COMBINATIONS AND KEYWORD OCCURRENCES – SCENARIO 5

Keyword	Occurrences	Total Link Strength
COVID-19	8370	7944
SARS-CoV-2	1855	1838
Management	1758	1727
Risk	1702	1680
Coronavirus	1259	1237
Impact	987	974
Pandemic	887	881
Mortality	731	724

Health	579	565
Outcomes	524	519
Infection	494	492
Care	45	444
COVID-19 Pandemic	485	436
Pneumonia	431	431
Disease	430	424

The table above shows some of the most often-used terms, including COVID-19, SARS-CoV-2, risk, coronavirus, impact, pandemic, mortality, infection, care, and outcomes.

CHAPTER 5 DISCUSSION

Data-driven decision-making plays a critical role in company strategies for crisis management. Business processes are moving to digital platforms as innovations develop and societies adapt to them. The trend of part-time employment is now the norm in the corporate sector since the sharing economy is regarded as being disruptive. While the sharing economy is founded on the use of underutilized or unused assets, it is also a business flow model for international trade where many people can either benefit from reduced costs for services or find employment. Finding out how data analytics would affect sharing economy firm operations during the COVID-19 epidemic is the aim of the dissertation study. The COVID-19 epidemic has an unthinkable, Black Swan effect on the world. Although before the pandemic, sharing economy services had made part-time employment the social norm, the workplace has changed due to stay-at-home instructions to reduce coronavirus transmission.

To accomplish the goals of the dissertation study, research issues were dealt with using visualization, computational data, and bibliometric analysis. Each research question's optimal response was determined by utilizing the appropriate methodological approach. According to their significance in addressing the research purpose, they were each responded to in turn.

Research Question #1: What was the economic performance of the sharing economy during the COVID-19 pandemic?

Regression analysis and the computational lognormal procedure both show arbitrary variations during the pandemic. The dissertation pilot study's lognormal pricing models for Airbnb (pages 83-84) and Uber (pages 84-85) both show conservative price modifications based on the daily traded share of volume. The models include modest incremental changes in the adjusted closing price based on the volume of shares traded. That is a conservative assessment of the magnitude of recent local changes. The adjusted closing price and daily share volume of trade may be seen to have a loose symmetric relationship. The predictive aggregate characteristic outperforms the actual price, even if the projected adjusted closing prices for Airbnb (pages 89 to 92 in the results section) and Uber (pages 92 to 95 in the results section) are comparable to the actual adjusted closing prices. The daily traded volume of shares can be adjusted by using indicators from the linear regression analysis model to get the optimal higher price for the closing price. The sharing economy had a positive outlook during the epidemic and based on the regression of the computational results of the dissertation study, the pricing of the financial shares of the companies may perform better. It is evident, sharing economy businesses have good management and rely on indicators to control business operations based on their technological ecosystem's computational processes.

Performance metrics (page 90 for Airbnb and page 93 for Uber): such as squared root mean error, relative error, and prediction average, show that the target attribute (Predicted Adjusted Closing Price) has a small marginal value error to the actual pricing under cross-validation methodology. That reflects that predictive analytics can be utilized in operational business activities. Based on their financial results, sharing economy businesses like Uber and Airbnb performed modestly during the pandemic. Aggregated dissertation study findings indicate that the performance of or addition to the data indicators they are employing in their technical infrastructure may be improved by predictive technologies.

Research Question #2: How was data analytics used in the sharing economy during the COVID-19 pandemic?

During the COVID-19 pandemic, data analytics was employed as a data-driven indication to manage their daily business operations. These activities include risk management techniques for improved financial results and safety precautions at the location where the service is provided to slow the spread of the coronavirus. Their real lognormal adjusted closing prices demonstrate robust economic success, and the use of predictive technologies can make sharing economy businesses more competitive. The benefits and drawbacks of data-driven decision-making for sharing economy businesses can be examined from the perspective of the bibliographic coupling of research articles. It is possible to identify each contribution and impact based on the case study keyword configurations.

a) What were the consequential advantages of data-driven decision-making during the COVID-19 pandemic?

The role of technology played an important factor in the workplace with the use of Geographical Information Systems and mobile app technology. According to the pilot study for the dissertation, using mobile devices for business communications and utilizing technology to manage human resources are becoming standards in the COVID-19 era. In the workplace and our social lives, contact tracing technology using mobile apps and geographic information systems is utilized to discover virus infections. While sharing economy's ecological applications are installed on mobile phones and this procedure is integrated into these apps, telecommunications technology played a significant role in the prevention and slowing down of coronavirus transmission. Rising technologies (such as wireless networking...) and artificial intelligence support supply chain models that are driven by AI are the major technological improvements.

The most popular search terms in the keyword arrangement case studies with a favorable outlook are decision-making, crisis management, artificial intelligence, education, coronavirus detection process, social media, internet of things, Twitter, deep learning, coronavirus detection process, health tourism, performance, trust, sustainability, model, and communication.

The issues that are most heavily stressed in the bibliographic coupling case studies, where these topics and study areas are closely related, include:

- Data-driven methods that include response time.
- Utilizing Artificial Intelligence (AI).
- Deploying a neural network for the prediction and detection of COVID-19 cases.
- A deep learning framework for identifying the epidemiology systems.
- Deployment of AI for supply chain in the technological infrastructure.

- Effective treatments of antiviral testing.
- Consumer trust for continued intention to use the sharing economy.
- Evaluation of the social norms in hospitality.
- Including organizational and friendly responses to COVID-19.
- Flexible structural supply chain design for supply-demand allocations.
- Investigation of agribusiness diversification and intentions.
- Post-pandemic strategies for tourism experiences and behavioral intentions.
- The clinical diagnosis and treatment of COVID-19.
- Management of cardiovascular disease (CVD) associated with coronavirus.
- Formation of an expert panel to develop evidence-based guidelines for the clinical management of adult patients with coronavirus disease, and preventative measures to fight the virus.
- Tele-activities, such as teleconferences and teleworks, cut down travel time.
- The relationship between tele-activities, the sharing economy, and developing mobility technologies, which together make up a common application platform.

Technology had a key role in both the most sustainable workplace and the avoidance of the virus in the workplace. Data-driven neural networks and artificial intelligence increased:

- The performance of the response time for the detection of the virus.
- Faster implementation of business operations.
- Optimal supply-demand allocations for the supply chain in the technological infrastructure.
- The use of feedback processes to boost trust and safety for sharing economy services.

- The use of technology to clinically diagnose and treat COVID-19.
- Find better treatment solutions for the management of cardiovascular disease (CVD) associated with coronavirus and for people with other chronic conditions.
- Post-pandemic strategies are enabled on service technology platforms of sharing economy to investigate consumer intentions and experiences.
- Human-computer interaction was improved between sharing economy employees and consumers.
- Contact tracing and feedback post technology have become an essential part of the risk management component of the service architecture.

The Internet of things and social media platforms like Twitter were crucial for the sharing economy communications during the outbreak. According to the study's findings, this contributed to an increase in the use of sharing economy services, particularly for secure and healthy tourism operations. The epidemic has increased the importance of technology in daily life. This is where data-driven decision-making based on feedback loops and indications comes into play. Our lives are affected going forward by this. Uber and Airbnb have employed predictive technologies, geolocation and contact tracing technology, rating systems, and operational safety actions to identify high-transmissible coronavirus sites. That is a cautious strategy for handling everyday operational tasks and reducing consumer anxiety for improved adaptability. Evaluation of the current business model for the sharing economy, current tactics and effective treatments for antiviral testing, and evaluation of the social norms in hospitality, including organizational and friendly responses to COVID-19 disease will increase consumer trust for continued intention to use the sharing economy.

b) What were the consequential disadvantages of data-driven decision-making during the COVID-19 pandemic?

The dissertation pilot study suggested that misinformation and preventive measures during the early phase of the COVID-19 pandemic affected the daily operations of the sharing economy. According to keyword arrangement case studies, sustainable tourism was one of the industry's most significantly impacted. Bibliographic coupling reveals that there are studies with a pessimistic outlook on things like infections, pneumonia, the economy, carbon monoxide emissions, and patient management with future treatments. Although technology enhanced the ability to make data-driven decisions, fear of the coronavirus and misinformation about the disease negatively affected the sharing economy's economic operations. The research results indicated that attitudes toward sharing economy leading to adoption intentions are strongly increased by functional, economic, and emotional factors during the pandemic.

The most frequently used terms in the keyword occurrence case studies with a negative outlook are disease, pandemic, SARS-CoV-2 virus, risk, health, resilience, model, politics, commerce, food security, stock returns, deep learning, health, spread, determinants, performance, crisis management, challenges, risk perception, tourism behavior, design, investment, health, outcomes, prevalence, pneumonia, anxiety, COVID-19, pandemic, mortality, infection, care, and outcomes.

We can see from bibliographical coupling and keyword analysis that society is concerned about health and safety, which has an impact on how people work. To manage day-to-day corporate operations, risk management has become a vital component of crisis management. Data analytics can use the determinants to identify potential problematic regions and then take necessary action based on those findings. As individuals became more concerned about mortality, infection rates, anxiety, and severe diseases like pneumonia, tourism behavior shifted negatively. The pandemic issues have influenced stock returns, and food security is now a key issue for communities. Because of the effects of the epidemic, crisis management methods' adaptability changed. Our daily work has changed to remote working due to safety precautions and procedures, and our lives have altered mostly due to our concern about viral transmission. Compared to traditional firms, sharing economy services are better able to adjust for part-time work and take the appropriate action. According to research, sharing economy services have superior adaptability for consumers and employers during pandemics, and these services will continue to develop in the future using data-driven decision-making.

Research Question #3: What preventive steps can be taken to improve data analytics as a crisis management tool in a post-pandemic world of sharing economy?

Since their founding, sharing economy services have grown to play a significant role in our lives. They are essential for the global economy because they allow for safer and more economical commercial operations. Travelers can use Airbnb to rent out convenient and economic rooms, and Uber to get quick and reasonable trips. Because of the COVID-19 epidemic, our daily lives, and the way we think have both changed significantly. Coronavirus's effects on a global, micro-to-macro scale affected the daily business operations of the sharing economy. To stop or slow the spread of the coronavirus, working remotely or from home has become the desired norm. Additionally, it was crucial for secure and healthy operations. Sharing economy services were impacted negatively by remote working since they rely on daily in-person interactions. They had to innovate new solutions for economic survivability. During this time, using a facial mask when in an Uber or Airbnb room and keeping hand sanitizer on hand at work have become essential. Social distance posed one of the major problems for the sharing economy, which required better solutions. These safety precautions included partitions in the Uber cars separating the driver and the passenger, cashless payment methods, constant face mask use throughout the services, and disinfection of the cars and rooms after each customer.

Technology played a significant role in identifying high-risk locations where coronavirus illness is extremely contagious or in user feedback and rating systems to match customers with better services. Based on contact tracing technology, geospatial information systems, and social media user comments have been crucial in detecting probable transmission locations. Data-driven indicators made it possible to take the appropriate action. Data analytics has evolved as a vital element of risk management in the sharing economy as risk management procedures are ubiquitous and conventional in financial business while crisis management became more significant in the post-pandemic era. Dissertation results suggested that predictive analytic performance has optimal financial performance. Objectives gained from the bibliographic coupling and keyword analysis showed increased importance of technology (e.g., mobile apps and contact tracing technology). Sharing economy businesses will continue to employ data-driven indicators to optimize their everyday company operations for a healthy and safe work environment in the post-epidemic world because of the lessons learned from the pandemic. When dealing with Black Swan events like pandemics, data-driven decision-making is a crucial tool, and predictive analytics can foresee similar catastrophes. Businesses' crisis management capacities will need to be more data-driven and based on forecasting technologies to prepare for probable pandemic-like situations. One recommended post-pandemic strategy is the formation of an expert panel to develop evidence-based guidelines for the clinical management of adult patients with coronavirus disease, and preventative measures to fight the virus. This was part of the research results that these expert suggestions can be important for similar future epidemics. Uber, Airbnb, and other sharing economy services can take advantage of these recommendations,

CHAPTER 6 CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

Based on evaluations of the bibliometric and financial data, the research's goals and questions are addressed. Each research objective and question is addressed, and the appropriate data collection technique is used.

6.1 CONCLUSIONS

The goal of this study is to perform a critical evaluation of the role of crisis management for the sharing economy services during the COVID-19 pandemic. Research findings suggest that in the post-pandemic era when the pandemic is over, there is a fear of similar viruses that represent health concerns. Remote working has become the norm in the workplace where technology plays an important role. Companies in the sharing economy employ data-driven decision-making indicators to increase operations' health and safety as well as their economic independence. Mobile communications and the feedback process of Service Enterprise Platforms are an important part of this. Risk management has become an essential business strategy for the sharing economy services as well as other businesses globally. Predictive Health Informatics can forecast, diagnose, and prevent similar health epidemics, and Data Analytics of sharing economy ecosystem can provide better suggestions for safe operations and improved profitability. Also noteworthy is the fact that each traditional and sharing economy business model will continue to develop and become better equipped for potential catastrophic events because of data-driven indicators and forecasting technology. On this basis, safe and wholesome company operations will be executed while we go about our daily lives, and customer confidence in sharing economy services will rise.

6.2 RECOMMENDATIONS

Black Swan is thought to be a systemic shock to financial markets and daily societal life that may change social standards. Data analytics are used in risk management as part of crisis management, where data-driven decision-making is given top importance to control and prevent such disruptions. The technical infrastructure of businesses, particularly sharing economy services, leverages these metrics to inform their employees and customers. Health informatics is important for predicting and diagnosing worldwide diseases. Based on the findings of the research, risk management ought to be a significant component of every technical component of a corporation. By taking the necessary precautions, upcoming black swan events can be prevented. It's also crucial to remember that the sharing economy has made part-time employment vital to supporting our way of life. As technology advances, business practices will depart from the norm and incorporate remote work practices.

Crisis management should be treated as a new domain of library and information science. This dissertation study is based on a case study about the effects of the COVID-19 pandemic on sharing economy and analyzing data-driven decision-making as predictive analytics for the services during this period. Risk management practices should be included in the scientific literature of library and information science to observe and forecast future similar crises.

6.3 LIMITATIONS AND FUTURE RESEARCH

The research results and findings were limited to the research objective of evaluating the data-driven crisis management for sharing economy. To reach reliable conclusions, each study goal and topic is assessed and researched utilizing the appropriate computational data-gathering methodology. The outcomes of the dissertation study only briefly examine related studies on data-driven indicators' employability for better decision-making, risk management practices of corporate technological services, and crisis management in Black Swan events. The study's goals are limited to examining similar findings and are transferable to other similar research projects. It can be a model for future research studies based on similar expectations and outcomes. For the library and information science literature to observe and predict future crises comparable to the ones we are experiencing now, risk management procedures should be included. According to the study's conclusions, crisis management ought to be a crucial component of library and information science when researching COVID-19 pandemic-related lessons for understanding future "Black Swan" catastrophes.

A new innovative methodological technique is developed while working on the research. New research fronts or factors that impact or contribute to a research objective can be identified using computer software tools (e.g., VOSViewer, or HistCite) based on bibliometric methods such as bibliographic coupling, co-citation analysis, citation analysis, and keyword occurrence. It is based on the shortest-path algorithm because the distance between edges reflects link strength. The number of times scientific articles are searched, cited, co-cited, or shared among researchers for their study objectives is determined by link strength. By examining the link strength of these most cited or shared articles, we can determine and evaluate important points. This analogy can be used in both future and current studies to investigate various study objectives or to provide better answers to questions by identifying important factors that can contribute to the desired outcome. This new technique can be viewed as an important supplement to existing bibliometric methodologies that can improve the quality of scientific articles.

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APPENDICES

APPENDIX 1: SUSTAINABILITY REPORT FROM UBER

The Uber ride-sharing company was founded in 2009 on an application platform (Blystone 2021). Today, it is one of the largest players in the ride-share market. Uber's technology changed how we work forever. Uber's global philosophy is based on a positive mandate with economic empowerment for employees, sustainable services with renewable energy, equal and accessible services for everyone, and safety through the technology platform (Uber 2021). Uber's response to COVID-19 for safe and healthy operations included encouraging riders to forgo unnecessary travel, providing health sanitization supplies to employees, supporting healthcare workers and first responders, and implementing crucial safety policies like covering one's face while using the service options or observing any symptoms of COVID-19 in a driver or rider.

APPENDIX 2: SUSTAINABILITY REPORT FROM AIRBNB

An online marketplace called Airbnb (ABNB) was established in 2007 to bring together those looking for lodging in particular areas and those looking to rent out their homes. It provides a convenient option for travelers to rent, as well as a means for landlords to make some money. Airbnb's philosophy is based on the following categories (Airbnb 2021):

a) The platform for hosts focuses on creating solutions to meet the diverse demands of hosts.
b) A globally trusted platform for guests offers a wide range of experiences and services through a mobile app and website.
c) A global culture that is upbeat and promotes empathy and the mission., as well as welcomes knowledge, experiences, and backgrounds.

d) Reducing carbon and other greenhouse gas emissions related to worldwide operations, environmental sustainability as a goal, and a commitment to operate as a Net Zero Company by 2030.

Appendix 3: RapidMiner Operator Definitions

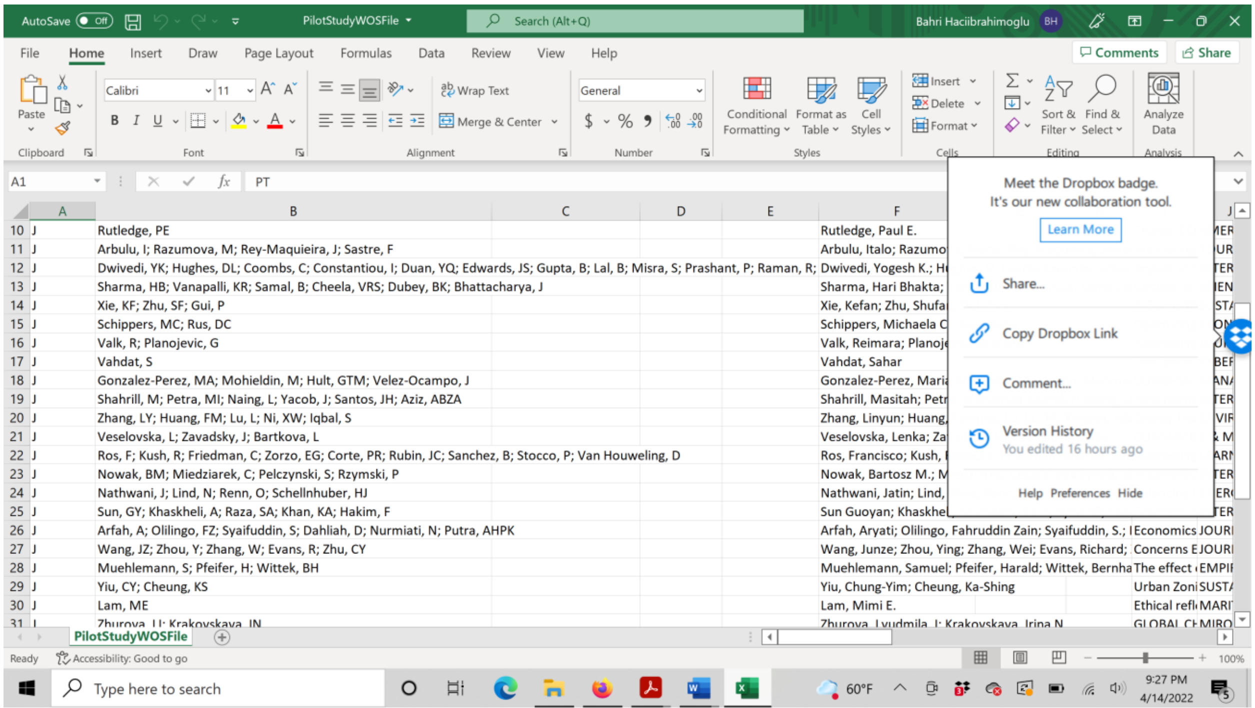
Linear Regression Operator: Regression is a mathematical prediction method. It is a statistical measure that seeks to ascertain the strength of the correlation between a single dependent variable (the label attribute) and several other varying variables known as independent variables (regular attributes) (RapidMiner 2022). Regression is used to predict a continuous value, just like classification is used to predict categorical labels. By fitting a linear equation to the observed data, linear regression seeks to model the connection between a scalar variable and one or more explanatory factors.

Performance (Regression) Operator: The Performance operator calculates the most typical criteria for each sort of learning task and determines it automatically (RapidMiner 2022). A good estimate of a model's performance on unknown data sets can be obtained by evaluating the model's performance on independent test sets.

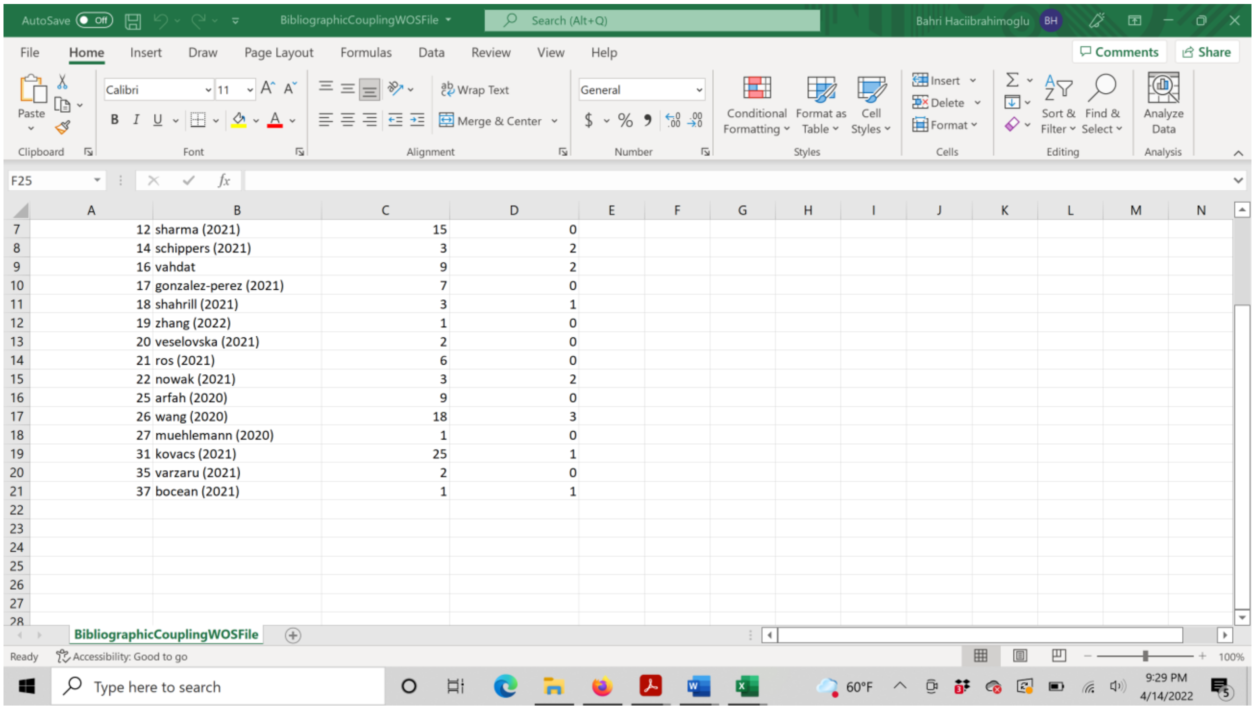
Cross Validation Operator: It is mostly used to predict how well a model (trained by a specific learning Operator) would function in the actual application (RapidMiner 2022). A Training subprocess and a Testing subprocess are two sub-processes. A model is trained using the Training subprocess. The Testing subprocess then uses the learned model. During the Testing phase, the model's effectiveness is evaluated. The example set is partitioned into k subsets of equal size, and the remaining k-1 subsets are used as the training dataset. The cross-validation process is then repeated k times, with each of the k subsets used exactly once as the test data.

Appendix 4: Excel files for the Dissertation Study

Excel File 1: Excel File with the Full WoS Records for the Pilot Study

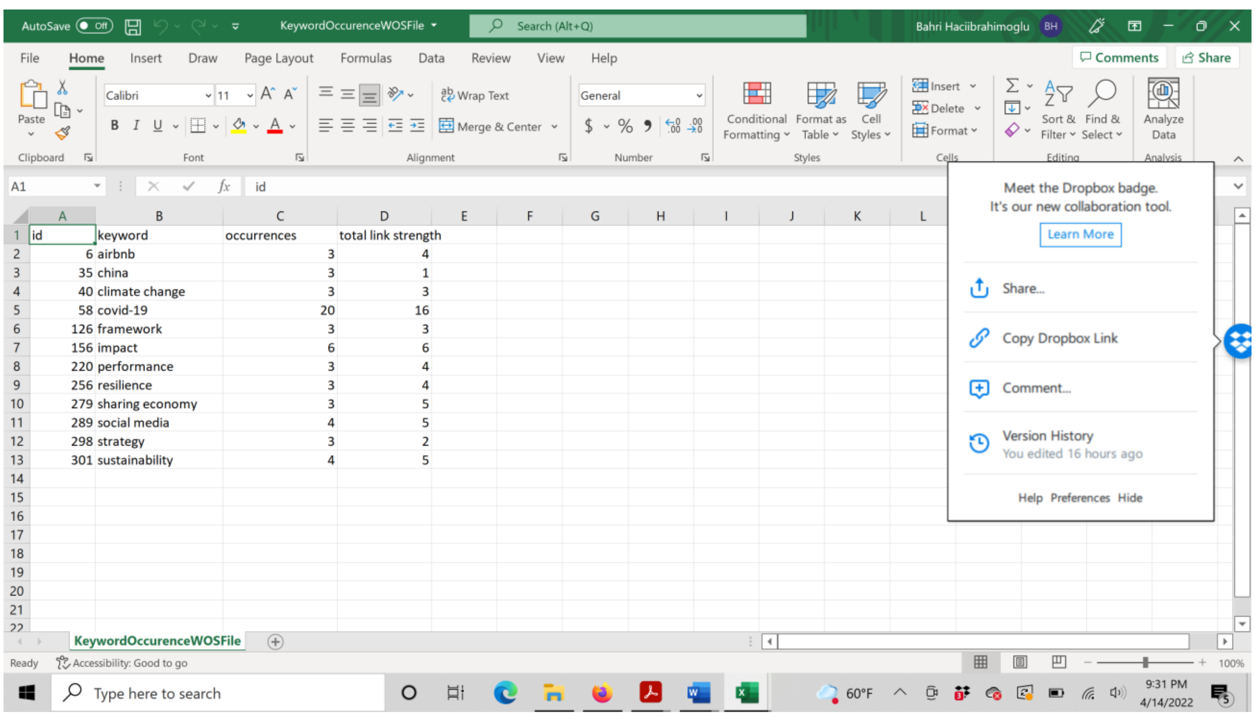


Excel File 2: WoS Bibliographic Coupling Spreadsheet File for the Pilot Study



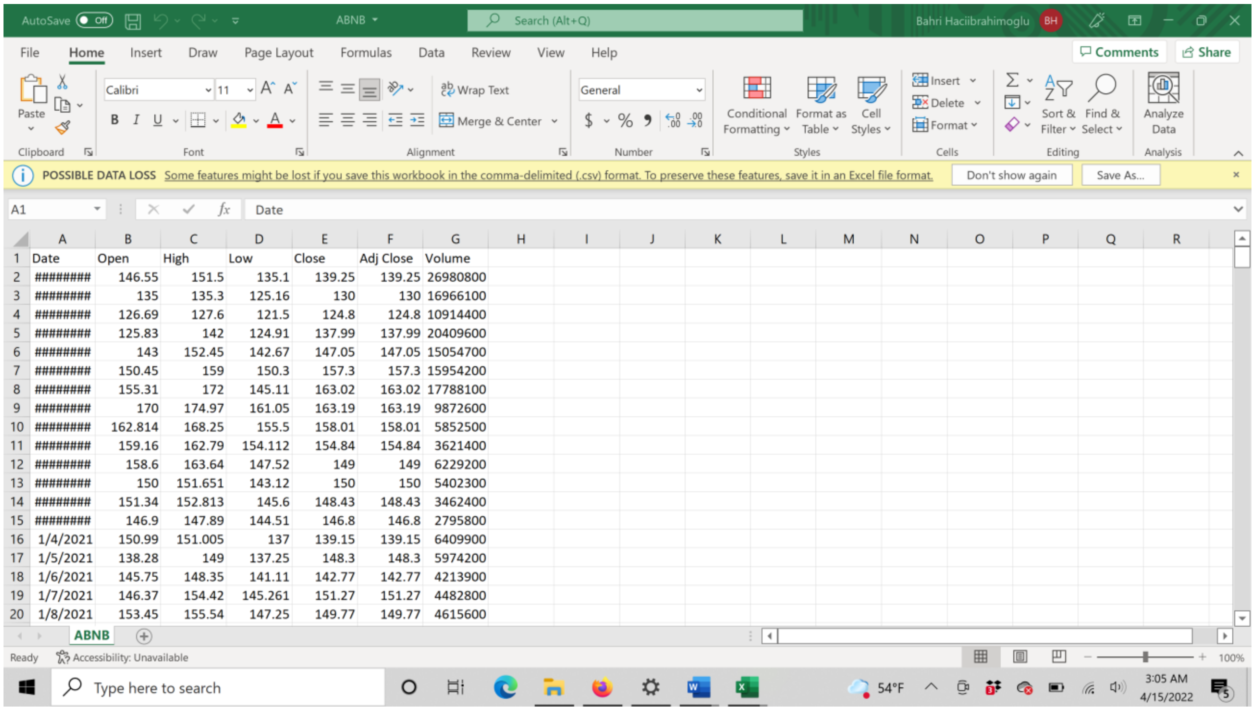
	A	B	C	D
7		12 sharma (2021)	15	0
8		14 schippers (2021)	3	2
9		16 vahdat	9	2
10		17 gonzalez-perez (2021)	7	0
11		18 shahrill (2021)	3	1
12		19 zhang (2022)	1	0
13		20 veselovska (2021)	2	0
14		21 ros (2021)	6	0
15		22 nowak (2021)	3	2
16		25 arfah (2020)	9	0
17		26 wang (2020)	18	3
18		27 muehlemann (2020)	1	0
19		31 kovacs (2021)	25	1
20		35 varzaru (2021)	2	0
21		37 bocean (2021)	1	1

EXCEL FILE 3: WOS KEYWORD OCCURRENCE EXCEL SPREADSHEET FOR THE PILOT STUDY



id	keyword	occurrences	total link strength
6	airbnb	3	4
35	china	3	1
40	climate change	3	3
58	covid-19	20	16
126	framework	3	3
156	impact	6	6
220	performance	3	4
256	resilience	3	4
279	sharing economy	3	5
289	social media	4	5
298	strategy	3	2
301	sustainability	4	5

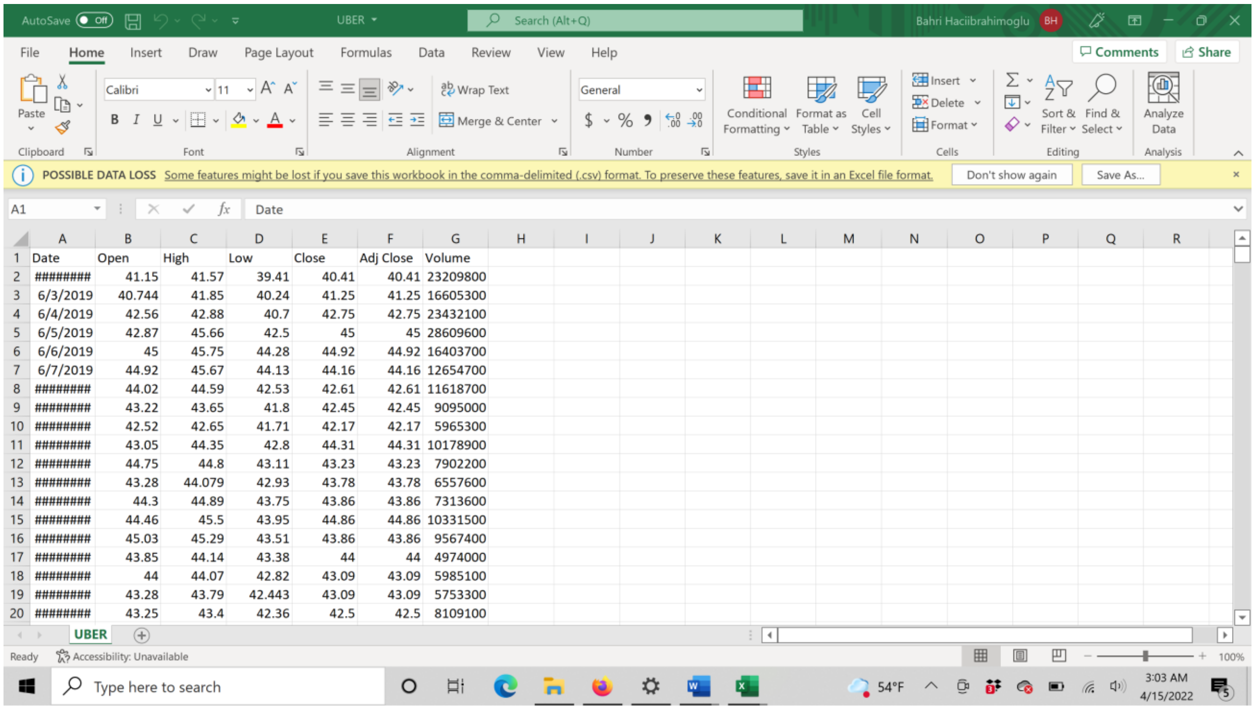
EXCEL FILE 4: AIRBNB'S HISTORICAL FINANCIAL PERFORMANCE EXCEL SPREADSHEET FOR THE PILOT STUDY – DURING THE COVID-19 PANDEMIC



	A	B	C	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	########	146.55	151.5	135.1	139.25	139.25	26980800
3	########	135	135.3	125.16	130	130	16966100
4	########	126.69	127.6	121.5	124.8	124.8	10914400
5	########	125.83	142	124.91	137.99	137.99	20409600
6	########	143	152.45	142.67	147.05	147.05	15054700
7	########	150.45	159	150.3	157.3	157.3	15954200
8	########	155.31	172	145.11	163.02	163.02	17788100
9	########	170	174.97	161.05	163.19	163.19	9872600
10	########	162.814	168.25	155.5	158.01	158.01	5852500
11	########	159.16	162.79	154.112	154.84	154.84	3621400
12	########	158.6	163.64	147.52	149	149	6229200
13	########	150	151.651	143.12	150	150	5402300
14	########	151.34	152.813	145.6	148.43	148.43	3462400
15	########	146.9	147.89	144.51	146.8	146.8	2795800
16	1/4/2021	150.99	151.005	137	139.15	139.15	6409900
17	1/5/2021	138.28	149	137.25	148.3	148.3	5974200
18	1/6/2021	145.75	148.35	141.11	142.77	142.77	4213900
19	1/7/2021	146.37	154.42	145.261	151.27	151.27	4482800
20	1/8/2021	153.45	155.54	147.25	149.77	149.77	4615600

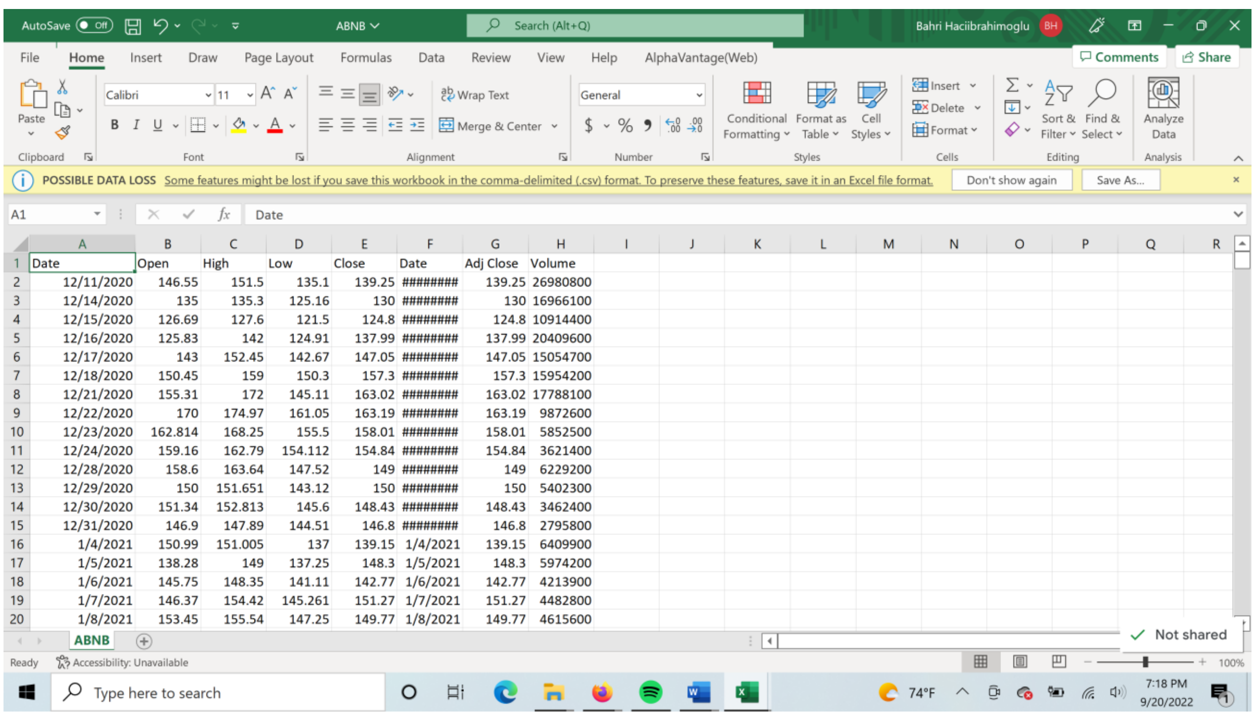
ABNB

EXCEL FILE 5: UBER'S HISTORICAL FINANCIAL PERFORMANCE EXCEL SPREADSHEET FOR THE PILOT STUDY – DURING THE COVID-19 PANDEMIC



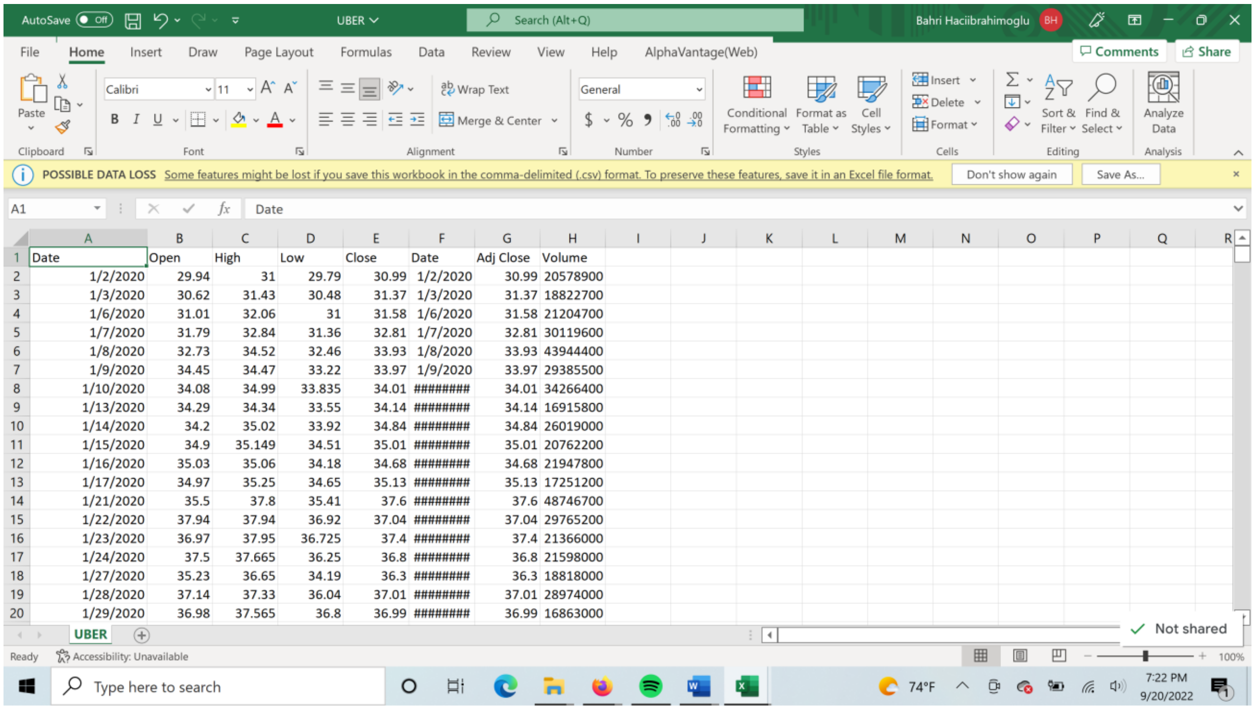
Date	Open	High	Low	Close	Adj Close	Volume
########	41.15	41.57	39.41	40.41	40.41	23209800
6/3/2019	40.744	41.85	40.24	41.25	41.25	16605300
6/4/2019	42.56	42.88	40.7	42.75	42.75	23432100
6/5/2019	42.87	45.66	42.5	45	45	28609600
6/6/2019	45	45.75	44.28	44.92	44.92	16403700
6/7/2019	44.92	45.67	44.13	44.16	44.16	12654700
########	44.02	44.59	42.53	42.61	42.61	11618700
########	43.22	43.65	41.8	42.45	42.45	9095000
########	42.52	42.65	41.71	42.17	42.17	5965300
########	43.05	44.35	42.8	44.31	44.31	10178900
########	44.75	44.8	43.11	43.23	43.23	7902200
########	43.28	44.079	42.93	43.78	43.78	6557600
########	44.3	44.89	43.75	43.86	43.86	7313600
########	44.46	45.5	43.95	44.86	44.86	10331500
########	45.03	45.29	43.51	43.86	43.86	9567400
########	43.85	44.14	43.38	44	44	4974000
########	44	44.07	42.82	43.09	43.09	5985100
########	43.28	43.79	42.443	43.09	43.09	5753300
########	43.25	43.4	42.36	42.5	42.5	8109100

Excel File 6: Airbnb's Historical Performance During the COVID-19 Pandemic – Excel Spreadsheet



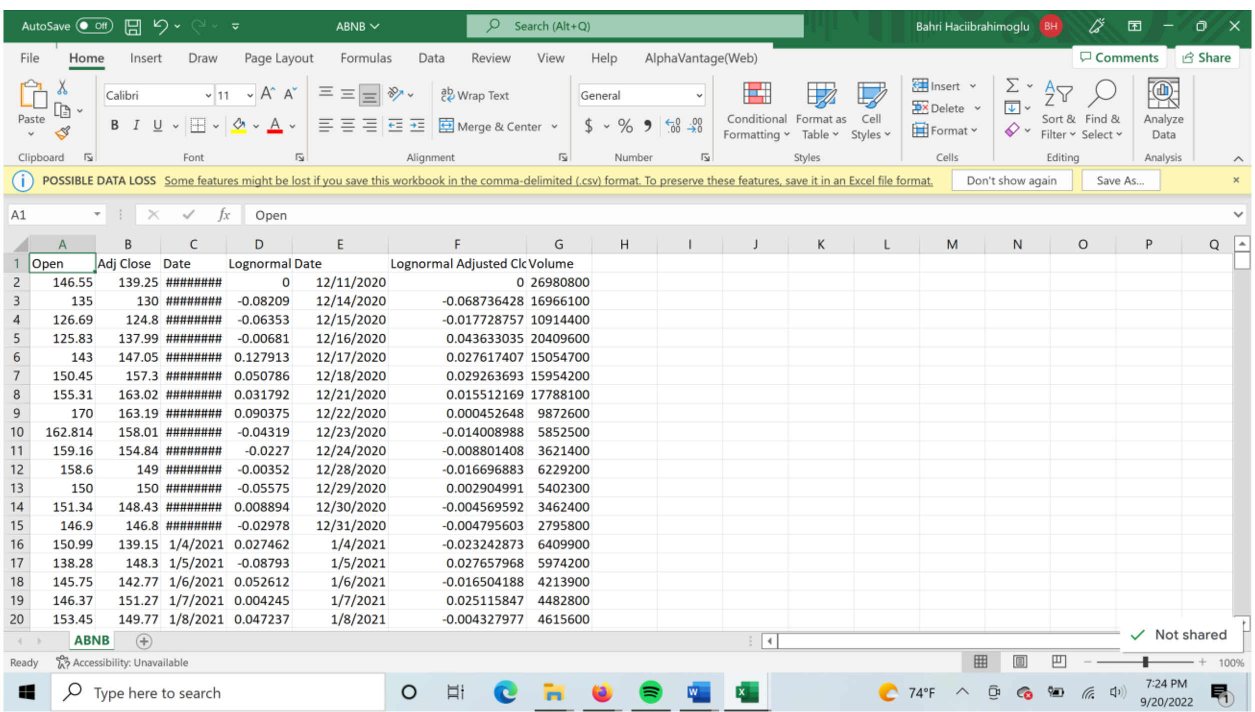
Date	Open	High	Low	Close	Date	Adj Close	Volume
12/11/2020	146.55	151.5	135.1	139.25	########	139.25	26980800
12/14/2020	135	135.3	125.16	130	########	130	16966100
12/15/2020	126.69	127.6	121.5	124.8	########	124.8	10914400
12/16/2020	125.83	142	124.91	137.99	########	137.99	20409600
12/17/2020	143	152.45	142.67	147.05	########	147.05	15054700
12/18/2020	150.45	159	150.3	157.3	########	157.3	15954200
12/21/2020	155.31	172	145.11	163.02	########	163.02	17788100
12/22/2020	170	174.97	161.05	163.19	########	163.19	9872600
12/23/2020	162.814	168.25	155.5	158.01	########	158.01	5852500
12/24/2020	159.16	162.79	154.112	154.84	########	154.84	3621400
12/28/2020	158.6	163.64	147.52	149	########	149	6229200
12/29/2020	150	151.651	143.12	150	########	150	5402300
12/30/2020	151.34	152.813	145.6	148.43	########	148.43	3462400
12/31/2020	146.9	147.89	144.51	146.8	########	146.8	2795800
1/4/2021	150.99	151.005	137	139.15	1/4/2021	139.15	6409900
1/5/2021	138.28	149	137.25	148.3	1/5/2021	148.3	5974200
1/6/2021	145.75	148.35	141.11	142.77	1/6/2021	142.77	4213900
1/7/2021	146.37	154.42	145.261	151.27	1/7/2021	151.27	4482800
1/8/2021	153.45	155.54	147.25	149.77	1/8/2021	149.77	4615600

Excel File 7: Uber's Historical Performance During the COVID-19 Pandemic – Excel Spreadsheet



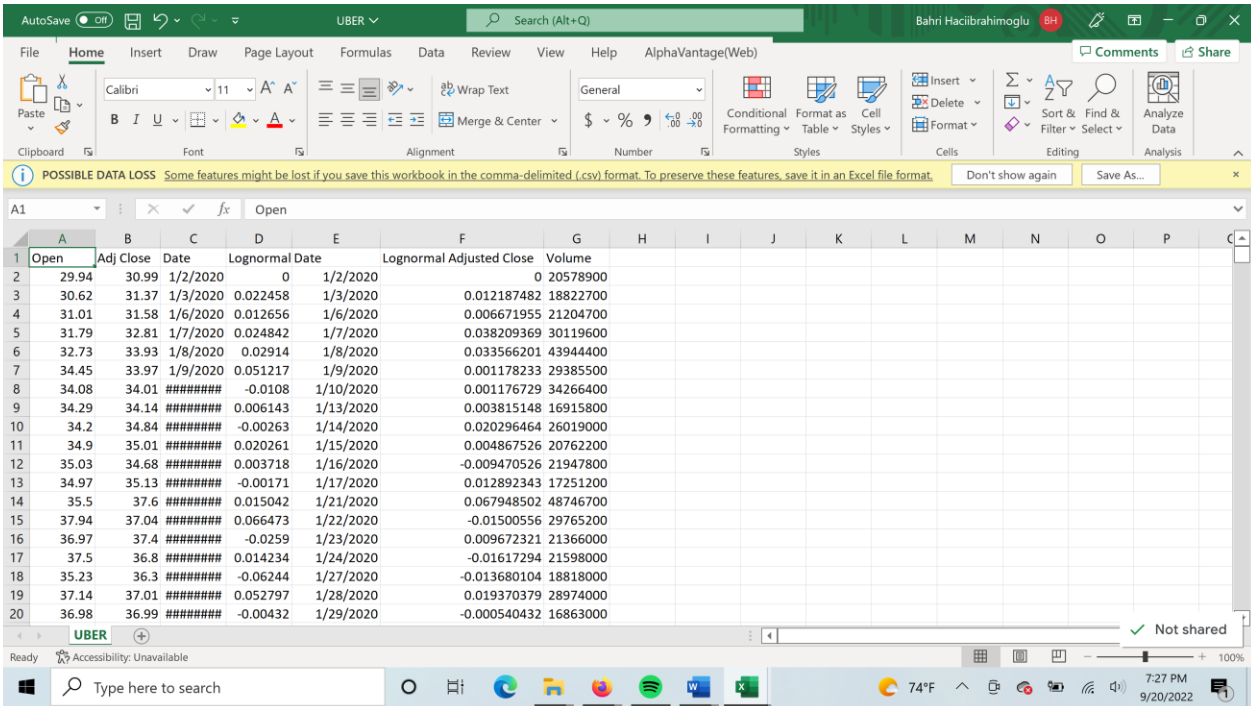
Date	Open	High	Low	Close	Date	Adj Close	Volume
1/2/2020	29.94	31	29.79	30.99	1/2/2020	30.99	20578900
1/3/2020	30.62	31.43	30.48	31.37	1/3/2020	31.37	18822700
1/6/2020	31.01	32.06	31	31.58	1/6/2020	31.58	21204700
1/7/2020	31.79	32.84	31.36	32.81	1/7/2020	32.81	30119600
1/8/2020	32.73	34.52	32.46	33.93	1/8/2020	33.93	43944400
1/9/2020	34.45	34.47	33.22	33.97	1/9/2020	33.97	29385500
1/10/2020	34.08	34.99	33.835	34.01	########	34.01	34266400
1/13/2020	34.29	34.34	33.55	34.14	########	34.14	16915800
1/14/2020	34.2	35.02	33.92	34.84	########	34.84	26019000
1/15/2020	34.9	35.149	34.51	35.01	########	35.01	20762200
1/16/2020	35.03	35.06	34.18	34.68	########	34.68	21947800
1/17/2020	34.97	35.25	34.65	35.13	########	35.13	17251200
1/21/2020	35.5	37.8	35.41	37.6	########	37.6	48746700
1/22/2020	37.94	37.94	36.92	37.04	########	37.04	29765200
1/23/2020	36.97	37.95	36.725	37.4	########	37.4	21366000
1/24/2020	37.5	37.665	36.25	36.8	########	36.8	21598000
1/27/2020	35.23	36.65	34.19	36.3	########	36.3	18818000
1/28/2020	37.14	37.33	36.04	37.01	########	37.01	28974000
1/29/2020	36.98	37.565	36.8	36.99	########	36.99	16863000

Excel File 8: Airbnb's Financial Performance During the COVID-19 Pandemic Based on Adjusted Closing Price



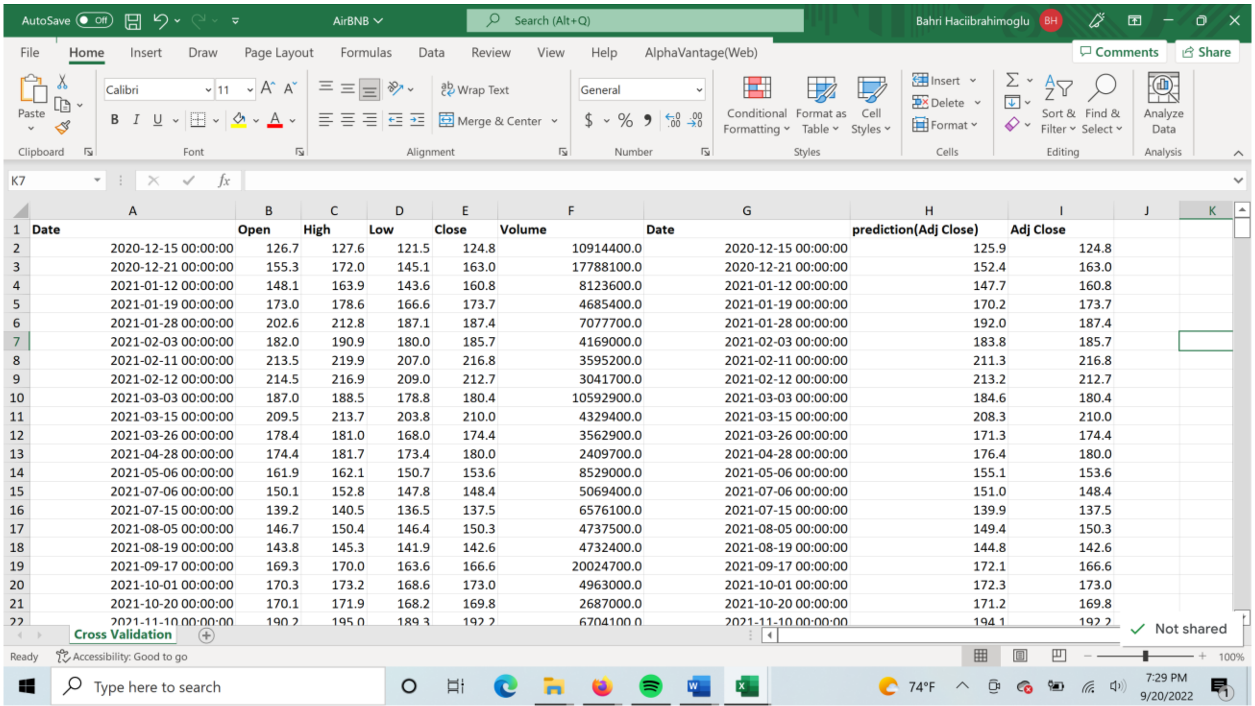
Open	Adj Close	Date	Lognormal	Date	Lognormal Adjusted Clc	Volume
146.55	139.25	########	0	12/11/2020	0	26980800
135	130	########	-0.08209	12/14/2020	-0.068736428	16966100
126.69	124.8	########	-0.06353	12/15/2020	-0.017728757	10914400
125.83	137.99	########	-0.00681	12/16/2020	0.043633035	20409600
143	147.05	########	0.127913	12/17/2020	0.027617407	15054700
150.45	157.3	########	0.050786	12/18/2020	0.029263693	15954200
155.31	163.02	########	0.031792	12/21/2020	0.015512169	17788100
170	163.19	########	0.090375	12/22/2020	0.000452648	9872600
162.814	158.01	########	-0.04319	12/23/2020	-0.014008988	5852500
159.16	154.84	########	-0.0227	12/24/2020	-0.008801408	3621400
158.6	149	########	-0.00352	12/28/2020	-0.016696883	6229200
150	150	########	-0.05575	12/29/2020	0.002904991	5402300
151.34	148.43	########	0.008894	12/30/2020	-0.004569592	3462400
146.9	146.8	########	-0.02978	12/31/2020	-0.004795603	2795800
150.99	139.15	1/4/2021	0.027462	1/4/2021	-0.023242873	6409900
138.28	148.3	1/5/2021	-0.08793	1/5/2021	0.027657968	5974200
145.75	142.77	1/6/2021	0.052612	1/6/2021	-0.016504188	4213900
146.37	151.27	1/7/2021	0.004245	1/7/2021	0.025115847	4482800
153.45	149.77	1/8/2021	0.047237	1/8/2021	-0.004327977	4615600

EXCEL FILE 9: UBER'S LOGNORMAL FINANCIAL PERFORMANCE DURING THE COVID-19 PANDEMIC BASED ON ADJUSTED CLOSING PRICE



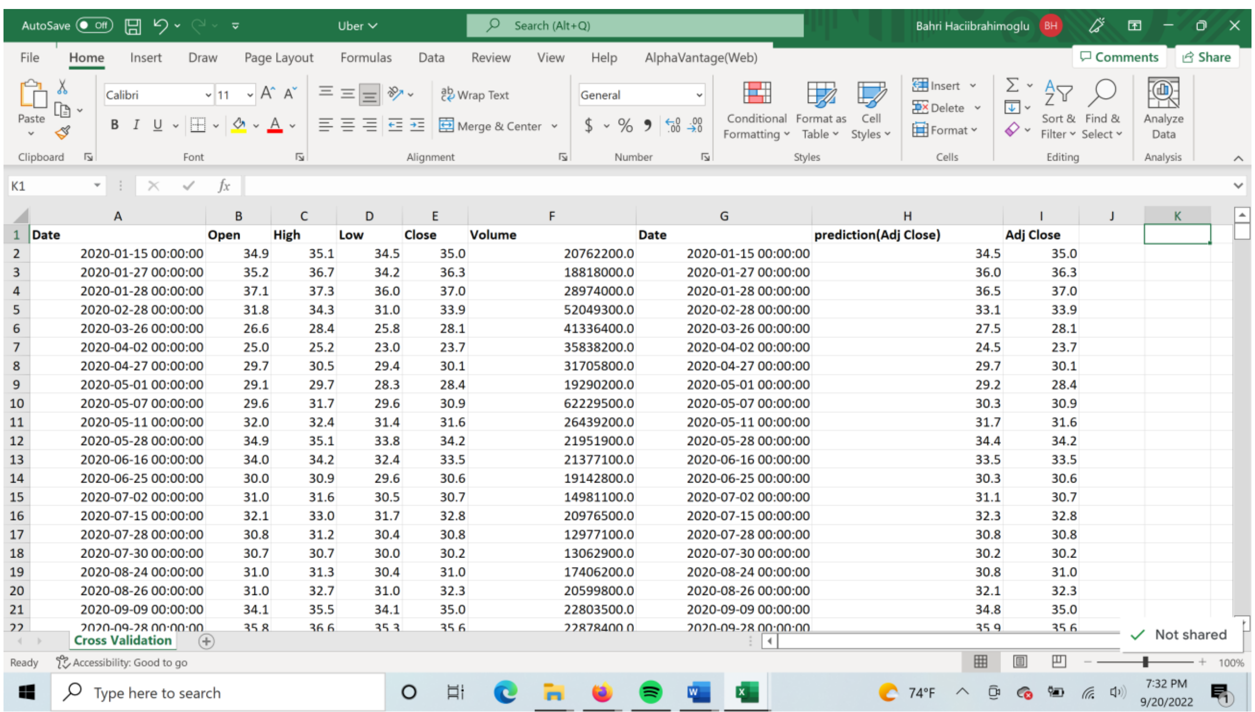
	A	B	C	D	E	F	G
1	Open	Adj Close	Date	Lognormal	Date	Lognormal Adjusted Close	Volume
2	29.94	30.99	1/2/2020	0	1/2/2020	0	20578900
3	30.62	31.37	1/3/2020	0.022458	1/3/2020	0.012187482	18822700
4	31.01	31.58	1/6/2020	0.012656	1/6/2020	0.006671955	21204700
5	31.79	32.81	1/7/2020	0.024842	1/7/2020	0.038209369	30119600
6	32.73	33.93	1/8/2020	0.02914	1/8/2020	0.033566201	43944400
7	34.45	33.97	1/9/2020	0.051217	1/9/2020	0.001178233	29385500
8	34.08	34.01	########	-0.0108	1/10/2020	0.001176729	34266400
9	34.29	34.14	########	0.006143	1/13/2020	0.003815148	16915800
10	34.2	34.84	########	-0.00263	1/14/2020	0.020296464	26019000
11	34.9	35.01	########	0.020261	1/15/2020	0.004867526	20762200
12	35.03	34.68	########	0.003718	1/16/2020	-0.009470526	21947800
13	34.97	35.13	########	-0.00171	1/17/2020	0.012892343	17251200
14	35.5	37.6	########	0.015042	1/21/2020	0.067948502	48746700
15	37.94	37.04	########	0.066473	1/22/2020	-0.01500556	29765200
16	36.97	37.4	########	-0.0259	1/23/2020	0.009672321	21366000
17	37.5	36.8	########	0.014234	1/24/2020	-0.01617294	21598000
18	35.23	36.3	########	-0.06244	1/27/2020	-0.013680104	18818000
19	37.14	37.01	########	0.052797	1/28/2020	0.019370379	28974000
20	36.98	36.99	########	-0.00432	1/29/2020	-0.000540432	16863000

EXCEL FILE 10: AIRBNB'S EXCEL SPREADSHEET BASED ON THE PREDICTED ADJUSTED CLOSING PRICE



Date	Open	High	Low	Close	Volume	Date	prediction(Adj Close)	Adj Close
2020-12-15 00:00:00	126.7	127.6	121.5	124.8	10914400.0	2020-12-15 00:00:00	125.9	124.8
2020-12-21 00:00:00	155.3	172.0	145.1	163.0	17788100.0	2020-12-21 00:00:00	152.4	163.0
2021-01-12 00:00:00	148.1	163.9	143.6	160.8	8123600.0	2021-01-12 00:00:00	147.7	160.8
2021-01-19 00:00:00	173.0	178.6	166.6	173.7	4685400.0	2021-01-19 00:00:00	170.2	173.7
2021-01-28 00:00:00	202.6	212.8	187.1	187.4	7077700.0	2021-01-28 00:00:00	192.0	187.4
2021-02-03 00:00:00	182.0	190.9	180.0	185.7	4169000.0	2021-02-03 00:00:00	183.8	185.7
2021-02-11 00:00:00	213.5	219.9	207.0	216.8	3595200.0	2021-02-11 00:00:00	211.3	216.8
2021-02-12 00:00:00	214.5	216.9	209.0	212.7	3041700.0	2021-02-12 00:00:00	213.2	212.7
2021-03-03 00:00:00	187.0	188.5	178.8	180.4	10592900.0	2021-03-03 00:00:00	184.6	180.4
2021-03-15 00:00:00	209.5	213.7	203.8	210.0	4329400.0	2021-03-15 00:00:00	208.3	210.0
2021-03-26 00:00:00	178.4	181.0	168.0	174.4	3562900.0	2021-03-26 00:00:00	171.3	174.4
2021-04-28 00:00:00	174.4	181.7	173.4	180.0	2409700.0	2021-04-28 00:00:00	176.4	180.0
2021-05-06 00:00:00	161.9	162.1	150.7	153.6	8529000.0	2021-05-06 00:00:00	155.1	153.6
2021-07-06 00:00:00	150.1	152.8	147.8	148.4	5069400.0	2021-07-06 00:00:00	151.0	148.4
2021-07-15 00:00:00	139.2	140.5	136.5	137.5	6576100.0	2021-07-15 00:00:00	139.9	137.5
2021-08-05 00:00:00	146.7	150.4	146.4	150.3	4737500.0	2021-08-05 00:00:00	149.4	150.3
2021-08-19 00:00:00	143.8	145.3	141.9	142.6	4732400.0	2021-08-19 00:00:00	144.8	142.6
2021-09-17 00:00:00	169.3	170.0	163.6	166.6	20024700.0	2021-09-17 00:00:00	172.1	166.6
2021-10-01 00:00:00	170.3	173.2	168.6	173.0	4963000.0	2021-10-01 00:00:00	172.3	173.0
2021-10-20 00:00:00	170.1	171.9	168.2	169.8	2687000.0	2021-10-20 00:00:00	171.2	169.8
2021-11-10 00:00:00	190.2	195.0	189.3	192.2	6704100.0	2021-11-10 00:00:00	194.1	192.2

Excel File 11: Uber's Excel Spreadsheet Based on the Predicted Adjusted Closing Price



Date	Open	High	Low	Close	Volume	Date	prediction(Adj Close)	Adj Close
2020-01-15 00:00:00	34.9	35.1	34.5	35.0	20762200.0	2020-01-15 00:00:00	34.5	35.0
2020-01-27 00:00:00	35.2	36.7	34.2	36.3	18818000.0	2020-01-27 00:00:00	36.0	36.3
2020-01-28 00:00:00	37.1	37.3	36.0	37.0	28974000.0	2020-01-28 00:00:00	36.5	37.0
2020-02-28 00:00:00	31.8	34.3	31.0	33.9	52049300.0	2020-02-28 00:00:00	33.1	33.9
2020-03-26 00:00:00	26.6	28.4	25.8	28.1	41336400.0	2020-03-26 00:00:00	27.5	28.1
2020-04-02 00:00:00	25.0	25.2	23.0	23.7	35838200.0	2020-04-02 00:00:00	24.5	23.7
2020-04-27 00:00:00	29.7	30.5	29.4	30.1	31705800.0	2020-04-27 00:00:00	29.7	30.1
2020-05-01 00:00:00	29.1	29.7	28.3	28.4	19290200.0	2020-05-01 00:00:00	29.2	28.4
2020-05-07 00:00:00	29.6	31.7	29.6	30.9	62229500.0	2020-05-07 00:00:00	30.3	30.9
2020-05-11 00:00:00	32.0	32.4	31.4	31.6	26439200.0	2020-05-11 00:00:00	31.7	31.6
2020-05-28 00:00:00	34.9	35.1	33.8	34.2	21951900.0	2020-05-28 00:00:00	34.4	34.2
2020-06-16 00:00:00	34.0	34.2	32.4	33.5	21377100.0	2020-06-16 00:00:00	33.5	33.5
2020-06-25 00:00:00	30.0	30.9	29.6	30.6	19142800.0	2020-06-25 00:00:00	30.3	30.6
2020-07-02 00:00:00	31.0	31.6	30.5	30.7	14981100.0	2020-07-02 00:00:00	31.1	30.7
2020-07-15 00:00:00	32.1	33.0	31.7	32.8	20976500.0	2020-07-15 00:00:00	32.3	32.8
2020-07-28 00:00:00	30.8	31.2	30.4	30.8	12977100.0	2020-07-28 00:00:00	30.8	30.8
2020-07-30 00:00:00	30.7	30.7	30.0	30.2	13062900.0	2020-07-30 00:00:00	30.2	30.2
2020-08-24 00:00:00	31.0	31.3	30.4	31.0	17406200.0	2020-08-24 00:00:00	30.8	31.0
2020-08-26 00:00:00	31.0	32.7	31.0	32.3	20599800.0	2020-08-26 00:00:00	32.1	32.3
2020-09-09 00:00:00	34.1	35.5	34.1	35.0	22803500.0	2020-09-09 00:00:00	34.8	35.0
2020-09-28 00:00:00	35.8	36.6	35.3	35.6	22878400.0	2020-09-28 00:00:00	35.9	35.6