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A Correlation Meta-Analysis of COVID-19 Shock, Intelligent Analytics, and Supply Chain Resiliency

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2024

Abstract

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by

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MS, National Defense University, 2005

BS, Mississippi State University, 1983

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Walden University

April 2024

Abstract

Supply managers are concerned that their supply chain resiliency (SCR) might be inadequate to protect their firms' supply networks from sudden disruptions, which could lead to significant cascading failures in their operations. Grounded in chaos theory, the purpose of this quantitative correlational study was to examine the relationships of COVID-19 and intelligent analytics (IA) with SCR. For meta-analysis of published findings, 41 studies published between 2019 and 2023 were selected for this study. The homogeneity test of COVID ES on SCR showed that the average ES was between small to medium size (d = .35), yet not consistent across the studies, $Q(23) = 41.31$, p =.011, $I^2 = 49.52$, $\tau^2 = .003$, $H^2 = 1.982$. Egger's meta-regression results for the effect size of COVID on SCR showed that the studies' publication year was a significant predictor (b = 0.041, t = 3.183, p = .004) while the studies' statistical method was not (b = .011, t = .325, p = .748). Only after accounting for these two study-level characteristics, the ES of COVID was homogeneous across all studies, $Q(22) = 31.120$, p = .072, $I^2 = 25.2$, τ^2 = .001, $H^2 = 1.337$. During the same period, the ES of IA on SCR was shown to be, on average, medium size (d = .634) and held consistent across the studies without accounting for any study-level characteristics, $Q(29) = 5.275$, p = 1, $I^2 = 0$, $\tau^2 = 0$, H^2 = 1.0. A key recommendation for supply chain managers includes developing adaptive and scalable supply chain resilience processes and implementing intelligent analytics to support supply chain decision-making. The implications for positive social change include the potential to provide stable employment opportunities and mitigate the effects of sudden supply chain disruption on consumers and the general public.

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Dedication

I dedicate this doctoral study to my mother, who encouraged me to pursue my dreams and reach for the stars. I especially want to dedicate this study to my wife, JC. She has encouraged, threatened, and provided a shoulder to support me. Last but not least, I would like to dedicate this study to my grandchildren. I provided an example to show them to pursue their stars and that no obstacle cannot be overcome with hard work and dedication.

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Section 1: Foundation of the Study

The COVID-19 pandemic has caused a temporal uncertainty shock, an unpredictable catastrophic event affecting various spheres of influence (Shin & Zhong, 2020). One of the major areas impacted by such shocks was the global supply chain, which was susceptible to disruption by factors such as environmental changes, natural disasters, and human-induced risks (Karl et al., 2018). The unprecedented decline in all economic factors, including credit lines, reserves, layoffs and furloughs, supply chains, and corporate bankruptcy, has been well documented by Elenev et al. (2020; Karl et al., 2018). Supply chain disruptions were common, with Razak et al. (2021) reporting that 65% of companies experience at least one disruption each year, resulting in substantial financial losses, such as over € 1 million in 2019. However, the impact of the COVID-19 pandemic on global economic uncertainty and disruption has been particularly significant, as highlighted by Salisu et al. (2020). The long-term implications of this crisis remain challenging to forecast, as Donthu and Gustafsson (2020) noted. The economic repercussions of the COVID-19 pandemic have been severe, with the US Bureau of Economic Analysis (2020) reporting a 5% fall in GDP in the first quarter of 2020, followed by a staggering decline of 31.7% in the second quarter. Profits from current production plummeted by $276.2 billion in the first quarter and $226.9 billion in the second quarter (US Bureau of Economic Analysis, 2020). These ongoing disruptions have made it impossible to quantify the overall cost of the COVID-19 pandemic accurately. According to the International Monetary Fund, the economic cost of the pandemic was estimated at $11 trillion (Kretchmer, 2020). This staggering figure aligns with other projections, which estimate the economic and monetary cost of the COVID-19 pandemic to range between $10 and $28 trillion by 2025 (Elliott, 2020). The COVID-19 pandemic has had a profound impact on the global economy, leading to significant disruptions in supply chains and causing a decrease in various economic factors (Ali & Rahman, 2021). The ongoing nature of the crisis makes it challenging to determine the exact monetary cost, but it was clear that the economic consequences were substantial.

Background of the Problem

The COVID-19 pandemic has had far-reaching implications for global supply chains, particularly downstream transportation and distribution (Ivanov & Das, 2020). The unprecedented nature of the pandemic has exposed the fragility of the global supply chain, highlighting the lack of operational agility in the delivery of products (Sarkis, 2020). To curb the spread of the virus, federal and state governments had implemented stringent stay-at-home measures, further disrupting supply chain operations (Dunn, 2021). Research indicates that the impact of COVID-19 on supply chains has been substantial. A study by Sherman (2020) revealed that 94% of Fortune 1000 companies reported severe disruptions to their supply chains due to the pandemic.

Similarly, Dunn (2021) found that in October 2020, 76% of the U.S. supply chain was affected by COVID-19. These statistics highlight the significant challenges for supply chain managers in navigating the turbulent, uncertain, and complex landscape induced by the pandemic (Van Hoek, 2020). Given these challenges, supply chain managers must develop resilient strategies to withstand nonlocalized temporal shocks. Research by Pugna et al. (2019) suggested that some supply chain managers lack sufficient understanding of intelligent analytics (IA) and its potential role in improving supply chain resilience (SCR). Specifically, supply chain managers may not fully understand how to leverage IA for actionable intelligence to build a resilient supply chain (Gordon et al., 2022). Supply chain managers must embrace IA and develop a deeper understanding of its application in forming resilient supply chains. By doing so, they can better navigate the challenges posed by future disruptions and ensure the smooth functioning of supply chain operations.

Problem and Purpose

The specific business problem was that some supply chain managers did not understand the relationship of COVID on SCR nor IA on SCR. The purpose of this quantitative correlation study was to examine the relationships between COVID on SCR and IA on SCR. The predictor variables were COVID and IA. The dependent variable was SCR. This study does not have a population in the traditional sense, as it was a random effect meta-analysis of the existing literature. The geographical location of this study was irrelevant.

Globalization of supply chains has led to intricate interdependencies between nations, enabling the exchange of raw materials, goods, components, and manufactured items (Bolatto et al., 2017; Xiao et al., 2019). In the global context of supply chains, disruptions in one geographical area can have far-reaching consequences, impacting the entire industry base and posing significant risks to all partners involved (Zeng & Yen, 2017). The repercussions of supply chain disruptions cascade downstream and upstream, potentially resulting in severe failures such as product scarcity, increased costs, and even company insolvency (Ivanov et al., 2014). It was essential to recognize that perturbations that occur in any region that serves as a source for the supply chain have global implications. As such, the location of this study was inherently global, as supported by the research of Elenev et al. (2020), Salisu et al. (2020), Donthu and Gustafsson (2020), and Ivanov and Das (2020).

Population and Sampling

This study analyzed the literature on global COVID on SCR and IA on SCR to better understand the effects. A random effect meta-analysis approach was used, which allowed a larger population size and a statistical correlation of the literature. By consolidating and quantifying a vast array of literature, a random effect meta-analysis offers a comprehensive overview of the topic, mainly when dealing with complex and conflicting information (Fokkens, 2019). The time period for this study spanned January 1, 2020, to December 30, 2023, to capture the most recent and relevant studies in the field. Establishing a predetermined selection criteria ensured the inclusion of pertinent literature. These criteria guided the selection of studies that met the acceptance criteria and were considered suitable for random effect meta-analysis (Moeyaert, 2019).

Nature of the Study

The quantitative research method was the most suitable approach for this study. This decision was based on several factors and supported by the findings of various scholars in the field. First, the ability to measure variable change was a vital advantage of the quantitative research method (Bridgmon & Martin, 2012). This method employs empirical techniques to investigate observable phenomena, as highlighted by Basias and

Pollalis (2018). Using statistical testing of variables, a quantitative research method allows for a rigorous and systematic data analysis (Almalki, 2016; Basias & Pollalis, 2018). The quantitative research method forms common themes across different domains, as Johnston et al. (2019) noted. It was a reliable and widely applicable method for studying various phenomena.

In contrast, qualitative methods focus on interpreting words, textual data, and the lived experiences of the participants (Bell & Wilmott, 2017; Saunders et al., 2019). While qualitative methods were valuable in their own right, they do not align with the empirical and statistical approach required for this study. Combining quantitative and qualitative methods, mixed-method research was inappropriate for this study. Şahin and Öztürk (2019) described mixed-method research as an approach that seeks to comprehensively understand the phenomenon by integrating quantitative data analysis and qualitative interpretation. This study measures the relationships between variables using statistical methods rather than interpreting individual experiences. The quantitative research method was the most suitable approach for this study due to its ability to measure variable change, its empirical nature, and its effectiveness in statistical testing. This method aligns well with the research objectives and will provide the necessary empirical evidence to address the research question.

A correlational research design was the most appropriate design. The choice of research design was based on the work of Seeram (2019), who established that correlational design was specifically designed to determine the predictions and relationships among the variables. By employing statistical measurements of relationships and strength, a correlational enables researchers to analyze evidence across multiple studies to identify commonalities (Mat Roni et al., 2020; Moeyaert, 2019). This type of design was particularly useful in consolidating and quantifying extensive and complex literature, as it allows for synthesizing information from various sources (Fokkens, 2019). Researchers can establish correlations and effect sizes (ES) by applying acceptance criteria to select relevant studies, enhancing the robustness of their findings (Moeyaert, 2019). A correlational provides a comprehensive and systematic approach to addressing research questions and examining relationships among variables.

Other quantitative designs, such as experimental and quasi-experimental designs, focus more on estimating the causal impact of changes in predictor variables on dependent variables (Saunders et al., 2019). Given the purpose of this study, which was to explore predictions and relationships rather than seeking cause and effect, a correlational research design was the most suitable approach. A correlational was chosen as the most appropriate methodology for this study. Correlational allows for analyzing relationships and predictions among variables while consolidating and quantifying diverse literature. By employing this design, the research aimed to provide a comprehensive and systematic understanding of the topic under investigation.

Research Question

RQ1: Is there a statistically significant relationship of (a) COVID on SCR and (b) IA on SCR?

Hypotheses

Null Hypothesis (H_0): There is no statistically significant relationship of COVID on SCR nor IA on SCR.

Alternative Hypothesis (H_1): There is a statistically significant relationship of COVID on SCR and IA on SCR.

Theoretical Framework

Using chaos theory as the framework for this study was a deliberate choice derived from the inherently chaotic nature of the COVID-19 pandemic. The pandemic exhibits characteristics that closely resemble the principles of the chaos theory, namely nonlinearity, non- predictability, and dynamism (Bonasera & Zhang, 2020). To gain deeper insight into chaotic systems, IA employs adaptive modeling techniques, providing a valuable tool for understanding the complexities of these systems (Mangiarotti et al., 2020).

The principles of chaos theory provide a theoretical lens through which the variables of uncertainty shock and intelligent analytical processes were examined, leading to interdependent outputs that can be correlated with the business supply chain (Ene, 2018). It was Lorenz (1993) who laid the groundwork for a comprehensive chaos theory, identifying uncertainty as a critical construct along with (a) instability, which refers to the sensitivity of systems to changes in their environment, (b) strange attractors, defined as the dynamic movement towards but never achieving equilibrium, and (c) emergent properties, which arise unpredictably from the interactions of individual components, were also established as integral components of chaos theory. Although the concept of deterministic chaos had been present in scientific and mathematical literature since the nineteenth century, it was not until Williams (1997) provided the necessary interpretation that a holistic chaos theory could be formed. Williams demonstrated how chaos theory elucidates the formation of correlational outcomes in observed nonlinear, unstable, and dynamic phenomena, particularly regarding temporal uncertainty shocks. In the context of this study, chaos theory aligns perfectly with the characteristics of uncertainty shock caused by the COVID-19 pandemic. The intelligent analytical systems employed in this research effectively model and capture these chaotic characteristics, enabling a comprehensive understanding of the complex dynamics at play. Chaos theory explains how shock phenomena can form correlational outcomes. Chaos theory and intelligent analytical systems model the characteristics of the uncertainty shock as applied in this study.

Operational Definitions

Effect size: A statistical measurement of relationship or practical significance. The higher the number, the stronger the relationship (Paul & Criado, 2020).

Intelligent Analytics: An artificial predictive system that was autonomous for parsing data to form probability of action; also known as artificial intelligence (AI), Intelligent Agents, machine learning algorithms, neural networks, big datasphere, and quantum computing (Bhargava et al., 2016).

Meta-analysis: A study of studies that provides a statistical implementation to synthesize evidence across studies to form a commonality (Gurevitch et al., 2018).

Nonlinearity: A dynamic formation that moves toward equilibrium but never reaches equilibrium and has no predictive nature (Issitt, 2018).

Supply chain resilience: The ability of the supply chain to react to dynamic disruptions while meeting demand. Agile, redundant, flexible, robust, cost-effective, scalable, and sustainable (Ali et al., 2021).

Assumptions, Limitations, and Delimitations

Researchers often strive to mitigate the inherent shortcomings of their studies by employing various strategies such as assumptions and delimitations. These techniques enable researchers to focus their study while reducing potential limitations. According to Dimitrios and Antigoni (2019), assumptions were crucial in shaping the statistical tests applied to the collected data. By making informed assumptions, researchers can refine their analysis and draw conclusions from the data (Raslan et al., 2020). Furthermore, Verma and Adbel-Salam (2019) emphasized the importance of acknowledging and addressing limitations in research. Researchers can ensure that their findings and interpretations are credible and reliable by being open and honest about constraints. Shahata (2018) highlighted how assumptions, limitations, and delimitations were pivotal in guiding the literature review process. These foundational elements establish the criteria for selecting relevant literature and provide a context for interpreting existing research comprehensively and systematically. Researchers employ assumptions, limitations, and delimitations to enhance the quality and rigor of their studies, strengthening the validity of their findings.

Assumptions

According to Nkwake (2020), assumptions are statements researchers believe to be true. In academic research, assumptions serve as foundational beliefs or premises on which the research was based. Assumptions are integral to the research process, as they guide the formulation of research questions, methodology, and interpretation (Nkwake, 2020). Researchers must critically evaluate and justify their assumptions, acknowledging the limitations and potential biases they may introduce. By articulating and defending their assumptions, researchers demonstrate their awareness of the underlying assumptions and biases that may influence their research results. Five assumptions were the basis for this research study as follows:

1. A meta-analysis synthesis forms a correlation across studies.
2. A single uncertainty shock provides generalization to other uncertainty shocks.
3. A chaotic lens view incorporates the variables of uncertainty shock, IA, and SCR.
4. The data in the literature were factual, with mitigated Type I and Type II errors.
5. There was sufficient literature to form a random effect meta-analysis.

Limitations

Limitations are inherent aspects of any research study that researchers cannot fully control (Theofanidis & Fountouki, 2019). Several limitations were acknowledged. The first limitation of this study was that it was based exclusively on published data.

There was the possibility of missing relevant unpublished data or ongoing research that could have provided additional information based solely on published sources. A second limitation was the reliance on the existing literature. Although the literature study offers a thorough overview of the subject, it was important to recognize that the current literature can restrict sample size, methodology, or bias. The ongoing COVID-19 pandemic poses a third limitation for this study. As the pandemic evolved, new research and data were constantly emerging. This makes capturing the most up-to-date information for a random effect meta-analysis challenging. Lastly, the use of free-access databases can be considered a fourth limitation. Although free-access databases provide a wide range of resources, they may not include all relevant studies or may have data availability or quality limitations.

Delimitations

Delimitations were crucial in research studies as they define the boundaries and scope within which the researcher operates (Theofanidis & Fountouki, 2019). Several delimitations have been implemented in this study to ensure a focused and effective investigation. The first delimitation involves the consideration of only one specific temporal period. This delimitation ensures that the research remains targeted and avoids potential confounding factors associated with changes over time. The second delimitation used in this study was a random effect meta-analysis approach. This methodology allows for synthesizing existing empirical studies to explore correlations between variables of interest. Using a random effect meta-analysis, I sought a more robust and comprehensive understanding of the research topic by examining a larger body of evidence. A third delimitation emphasized in this study was proxies to measure the variables under investigation. Proxies were widely used in research when direct measurement was challenging or impossible. This study aimed to capture the essence of the variables while acknowledging the limitations associated with their indirect measurement using proxies. Lastly, the fourth delimitation involves considering a global geographical area. The study aimed to explore the research topic in a broader context by taking a global perspective, capturing diverse perspectives and potential variations across different regions. This delimitation allows for a more comprehensive analysis and generalizability of findings beyond a specific locality.

Significance of the Study

In this quantitative correlational study, my objective was to establish a statistically significant correlation between COVID and IA as predictor variables and SCR as the dependent variable. This research effort can potentially contribute value to business practices and positive social change. This study may provide a future roadmap to preparing for uncertainty shocks and implementing IA systems into the decision loop to understand and minimize risk during periods of uncertainty.

I conducted a random effect meta-analysis of the existing literature, as D. Jackson and Turner (2017) suggested. A random effect meta-analysis provides the researcher with a tool for a strong and thorough understanding of the research issue. This powerful statistical tool allows me to investigate the correlations between predictor and dependent variables in several studies. By analyzing various studies, I can shed light on how companies respond to chaotic shocks, for instance, the unprecedented uncertainty caused by the COVID-19 pandemic.

Understanding the chaotic nature of COVID-19 and its implications for supply chain resiliency, solvency, and positive social change was paramount. Through this research, I uncovered insights to help businesses adapt and innovate their supply chain strategies to better withstand and recover from uncertain shocks. By identifying patterns and trends in the literature, I established generalizations and contributed to developing new paradigms for resilient supply chains in the face of uncertainty. Resilient supply networks can guarantee the availability of necessary goods and services during emergencies, reducing the adverse effects on society.

Contribution to Business Practice

The results of this study on business may lead to resilient supply chains adaptable to extreme temporal uncertainty shocks and draconian government reactions to lock down the country. New innovative supply chain solutions may form transportation, production, global interactions, and government involvement as more high-impact uncertainty shocks are learned (Sarkis, 2020). The COVID-19 uncertainty shock was an unpredicted opportunity for the supply chain exposure of shortcomings that could have gone unnoticed (Zhu et al., 2020).

The results of this research could have significant consequences for businesses, especially in supply chain management. The study suggests that developing resilient supply chains that can adapt to extreme temporal uncertainty shocks and withstand draconian governmental reactions, such as nationwide lockdowns, was crucial. Supply chain managers must understand the vulnerabilities in their supply chains to provide viable, realistic solutions for overcoming and adapting to uncertainty.

In light of the ongoing COVID-19 pandemic, which has created unprecedented uncertainty in the business environment, the study highlights the importance of innovative supply chain solutions. These solutions should encompass various aspects of the supply chain, including transportation, production, global interactions, and government participation (Sarkis, 2020). By continuously learning from high-impact uncertainty shocks, businesses can proactively shape their supply chains to be more resilient and responsive to future disruptions.

Zhu et al. (2020) noted that the COVID-19 pandemic has unexpectedly allowed supply chains to expose existing shortcomings. The disruptions caused by the pandemic have brought to light vulnerabilities that may otherwise have gone unnoticed. This revelation underscores the need for businesses to reassess and strengthen their supply chain strategies to ensure greater resilience in the face of future uncertainties. Business supply chain leaders can use this study to highlight the importance of building resilient supply chains that can withstand unexpected disruptions and adapt to government interventions. It underscores the need for businesses to embrace innovation and continuously learn from disruptive events such as the COVID-19 pandemic. In doing so, organizations can improve their ability to navigate uncertain times and maintain operational continuity.

Implications for Social Change

The results of this study may cause significant positive social change by establishing resilient supply chains that actively consider and implement solutions to mitigate the impacts faced by individuals and communities during periods of uncertainty. The ongoing COVID-19 pandemic presents a unique opportunity to explore how business leaders can make informed decisions in supply chain management, thus alleviating social burdens (He & Harris, 2020). By embracing new paradigms in supply chains, there may be the emergence of new social interaction norms (Ratten, 2020).

The development of resilient supply chains holds the promise of benefiting society and promoting economic and social stability during times of uncertainty. Achieving this goal can be accomplished through a range of strategies, including (a) fostering open, transparent, and timely communication to alleviate anxiety associated with uncertainty shocks; (b) swiftly reallocating production capacity to meet the demand for essential commodities during such shocks; (c) facilitating the rapid development of robust health systems to combat pandemic-related uncertainty shocks effectively; (d) scaling up production capabilities to meet the accelerated needs during times of uncertainty; (e) contributing to community emergency response funds through donations; (f) leveraging corporate intelligence and artificial intelligence systems to accelerate research and understanding of uncertainty shocks, and ultimately, devising effective solutions; and (g) reducing the financial burdens faced by individuals and communities during times of uncertainty (He & Harris, 2020).

A Review of the Professional and Academic Literature

A literature review plays a fundamental role in any research study and was vital in establishing the depth of knowledge on a particular research topic. By meticulously examining the existing literature, the researcher expands on the knowledge base of previous study findings and gains invaluable insights into the subject matter (Paul & Criado, 2020). By conducting a comprehensive review of the literature, researchers can effectively map and access the body of research conducted by their predecessors, thus substantiating their hypotheses and justifying the importance of their study (Snyder, 2019).

The significance of conducting a literature review cannot be overstated. It allows researchers to familiarize themselves with the existing literature, identify knowledge gaps, and determine the most appropriate methodology for their study. Furthermore, it enables researchers to build on previous findings, challenge existing theories, and contribute to advancing knowledge in their respective fields. By delving into previous researchers' works, a literature review provides a solid foundation for developing research questions and formulating hypotheses. The literature review helps the researcher critically assess the strengths and limitations of previous studies, identify potential biases or methodological flaws, and refine their research design accordingly.

A literature review serves as a means of acknowledging and giving credit to the researchers who have made significant contributions to the field. Citing their work, the researcher acknowledges the intellectual lineage and fully understands the subject matter.

This quantitative correlational study examines the connections of COVID on SCR and IA on SCR. The predictor variables in this study were the COVID and IA, while the dependent variable was SCR. The null hypothesis of this study does not posit a statistically significant relationship of COVID on SCR nor IA on SCR. The alternative hypothesis suggests a statistically significant relationship between these variables.

The literature review for my study involved a comprehensive search across multiple sources, including journal articles, government reports, and books. To search, I used various databases such as IEEE, Emerald Insights, Google Scholar, Science Direct, Applied Science, Elsevier, Taylor & Francis, ResearchGate, Wiley, Springer, Bureau of Economic Analysis, Walden University Library, Federal Reserve, International Monetary Fund, and National Bureau of Economic Research. The search examined the relationship between chaos theory, COVID, IA, and SCR and explored using random effect meta-analysis in the study. The literature review provides a background on chaos theory and justifies its selection as the theoretical framework for the study. I discussed other theoretical applications and highlighted the suitability of chaos theory for this particular research.

Using proxy measurements established the predictor variables COVID and IA, and the SCR dependent variable. The merits of a random effect meta-analysis to consolidate multiple studies across different domains into a single study were also discussed. To visually represent the references used in the literature review, Table 1 presents the reference numbers and the corresponding percentages.

Table 1

Summary of Literature Review References

References	Numbers	% of References
Peer-Reviewed	124	95%
Books	9	7%
Published on or after January 2019	118	90%
Total	131	100%

Chaos Theory

Lorenz (1993) was widely recognized as the pioneering figure in Chaos theory, significantly contributing to its development. Lorenz initially aimed to use computers as a meteorologist to forecast weather patterns. However, his experiments failed to produce accurate predictions, leading him to uncover a fundamental principle of chaos theory. This principle suggests that chaotic systems, characterized by their instability, were highly sensitive to even the slightest environmental changes, which can result in significant and unpredictable effects. Lorenz introduced the concept of the "butterfly effect," which refers to the notion that a slight perturbation, a butterfly flapping its wings, can lead to a significant event, like a hurricane, in a distant location. This idea highlights the interconnectedness and inherent unpredictability of chaotic systems. Lorenz also identified several critical constructs of chaos theory, including uncertainty, instability, strange attractors, and emergent properties.

Uncertainty was a fundamental characteristic of chaotic systems, as the behavior cannot be precisely determined due to the sensitivity to initial conditions. Instability further emphasizes the unpredictability of these systems, as even minor changes can lead to significant deviations from expected outcomes. Strange attractors describe the tendency of chaotic systems to approach but never reach a state of equilibrium, constantly evolving and exhibiting complex patterns. Lastly, emergent properties refer to the phenomenon where the behavior of the system as a whole cannot be predicted solely based on the knowledge of its individual components.

Chaos theory is a branch of science that deals with unpredictable and non-linear systems (Pryor et al., 2022). It was used when traditional linear and cause-and-effect models were insufficient to describe chaotic actions. Researchers such as Boeing (2016) and Famourzadeh and Sefidkhosh (2019) have highlighted the nature of chaos theory as the study of unpredictable systems with non-linear behavior. Oestreicher (2022) argued that chaos theory emphasizes the presence of order in phenomena that may appear disorderly. This was because the researcher may not have access to all the information necessary to comprehend the underlying patterns fully. Kovalevskaia et al. (2021) have shown that chaos theory was often employed to analyze statistical data related to nonlinear interactions within a system. Ene (2018) proposed that chaos theory provides a theoretical framework for understanding the interdependent outputs derived from the variables of uncertainty shock and intelligent analytical processes, particularly in the context of the business supply chain.

Regarding historical contributors, Anaxagoras, in 456 BCE, made significant contributions to fractality calculations for dynamic systems. Maxwell, 1882, and Poincaré, 1889, introduced the concept of initial conditions sensitivity, which was crucial in chaos theory. T. Li and Yorke (2004) coined the term "chaos" in their paper on period three, implying chaos, while Ruelle (2020) introduced the term "strange attractors." Finally, Lorenz (1993) laid the foundation for a holistic understanding of chaos theory.

According to Williams (1997), Zaminpira et al. (2019), and Letellier et al. (2021), chaos theory has been discussed in scientific and mathematical literature since the nineteenth century, but it lacked a comprehensive interpretation. Williams (1997) asserted that chaos theory provides insights into how nonlinear, unstable, dynamic, and sensitive phenomena can generate correlational outcomes. In chaos theory, reality was considered independent of the observer (Aslan et al., 2021; Famourzadeh & Sefidkhosh, 2019) and emphasizes the nonlinear effects on causal predictions (Fuller et al., 2020). M. Jackson (2020) and Fuller et al. (2020) proposed that chaos theory exists between order and disorder, offering patterns and predictive outcomes. The literature on chaos theory can explain complex and dynamic phenomena (Ruiz Estrada, 2021), enabling researchers to make predictions about non-linear phenomena (Fuller et al., 2020). Kovalevskaia et al. (2021) suggested that chaos theory can contribute to developing new paradigms for social and political responses to uncertain events. In the social sciences, chaos theory was employed to analyze non-linear chaotic phenomena, such as the COVID-19 pandemic, and to develop AI algorithms for a deeper understanding of these phenomena (Harris, 2021; Oestreicher, 2022).

Kernick (2018) asserted that chaos theory provides a valuable framework for understanding complex systems. Within this framework, researchers can analyze unpredictable nonlinear dynamic systems (Chen, 2021). Pryor et al. (2022) highlighted chaos as the dynamic interplay of stability, change, pattern, variation, and constancy, allowing for a more profound understanding and solvability of these systems. Additionally, chaos theory holds significant intrinsic value in social sciences (Mbengue et al., 2018).

Lorenz (1993) famously introduced the butterfly effect concept, in which an insignificant event, such as a butterfly flapping its wings, can have profound consequences, such as the formation of a hurricane on the other side of the world. The butterfly effect exemplifies the nonlinearity and sensitivity to initial conditions inherent in chaotic systems.

Chaos theory offers a valuable framework for studying unpredictable and non-linear systems, addressing the limitations of linear models, and offering insights into complex phenomena. Historical development and contemporary applications contribute to a deeper understanding of chaos theory's significance in various fields of study.

Chaos Theory and COVID-19

Chaos theory provides a valuable framework for understanding the COVID-19 pandemic. By examining the literature on chaos theory, one can gain insight into the phenomena's dynamic, chaotic, and complex nature (Ruiz Estrada, 2021). Researchers have applied chaos theory to explore the implications of COVID-19 across various business domains, establishing it as a theoretical lens and framework (Altinary & Kosak, 2021; Zhang et al., 2020). Chaos theory enables the modeling of the nonlinearity exhibited by COVID-19, as demonstrated by Mohammadi and Kouzehgari (2020), Del Chiappa et al. (2021), and Postavaru et al. (2021). Ozdemir et al. (2021) suggested that chaos theory forms the basis for new paradigms in understanding COVID-19 disruptions. In particular, one of the key constructs of chaos theory was strange attractors, which elucidate how order can emerge from chaotic states, thus influencing the evolution of COVID-19 mutations (Kumar & Sharma, 2021).

Chaos Theory and Intelligent Analytics

Chaos theory offers a valuable approach to optimizing IA systems over evolutionary time steps in chaotic systems (Sasdelli et al., 2020; Zhou et al., 2018). Dynamic, chaotic systems pose a challenge in predicting future states and their chaotic timescales (Sasdelli et al., 2020). By leveraging the principles of chaos theory, researchers can develop novel algorithms for IA systems to improve the predictability of future dynamic chaotic states (Sasdelli et al., 2020; Wang, 2018). The integration of chaos theory into IA yields more robust solutions for chaotic non-linearity systems (Ewees & Abd Elaziz, 2020; Kamboj et al., 2020). Combining IA and deterministic chaos theory allows accurate time-series forecasting (Xuan et al., 2019). In programming IA constructs with chaos theory influences, researchers can effectively address predictive modeling challenges in chaotic systems (Aslan et al., 2021).

Alternate Theories

In conducting this study on the relationship of COVID on SCR and IA on SCR, I explored several alternative theoretical frameworks. Specifically, I examined four theories: paradox theory, uncertainty theory, complexity theory, and uncertainty management theory (UMT). These theories were considered potential lenses to understand the dynamics and implications of COVID on SCR and IA on SCR. Each theory offers unique perspectives and insights that contribute to understanding the phenomenon. Considering these alternative theoretical frameworks, this study aims to comprehensively and robustly analyze the intricate interaction of COVID on SCR and IA on SCR.

Paradox Theory

Russell (1903) was credited with establishing the development of paradox theory. He introduced vital concepts such as duality, interdependence, contradiction, and believability. Tolstaya and Bestebreurtje (2021) highlighted Russell's paradigm that all outputs arise from contradiction and can be analyzed using classical logic. In today's complex business environments characterized by increased interaction, globalization, disrupted technologies, and uncertainty, supply chains face a paradoxical dichotomy of demands that influence decision-making strategies (Waldman et al., 2019). These paradoxical tensions, rooted in duality, were inseparable (Keller et al., 2021). The dominant assumption in paradox theory was the dynamic equilibrium model (Cunha & Putman, 2019; Ivory & Brooks, 2018). Calabretta et al. (2017) argued for a new paradigm combining the duality construct ends of the paradox with acceptance to influence supply chain decisions. The paradox theory significantly impacts the resilient supply chain through decision-making processes (Bellamy et al., 2019). Decision-makers used paradox theory to leverage existing competencies and explore new opportunities (Carter et al., 2020). Moreover, decision-makers use paradox theory to maintain balance amidst dichotomies in turbulent environments (Zehendner et al., 2021).

The field of paradox was expanding, leading to a better understanding of the nature and management of paradoxical stressors. According to Waldman et al. (2019), the complex globalization of industries and the presence of competing demands contributed to the emergence of paradoxical tensions and stressors. At the micro-level, new theories on paradox provide valuable insights into how individuals navigate these pressures. Waldman et al. further suggested that individuals with a paradoxical mindset and insight can propose innovative solutions by challenging existing paradigms.

In their study, Wilhelm and Sydow (2018) argued that the contradictory duality elements of paradox theory were both believable and logical. The authors emphasize the importance of understanding the tensions between competition and cooperation in the supply chain for supply chain managers to make informed decisions. They put forth three premises that supply chain managers must accept: the need to create synergies within the duality elements, the recognition that both elements were necessary to form synergistic outcomes, and the understanding that the duality cannot be easily analyzed and requires long-term study. Overall, Wilhelm and Sydow's findings highlight the complexity of managing paradoxes in the supply chain and the significance of embracing the tensions to achieve optimal outcomes.

In their study, Bellamy et al. (2019) argued that sustainability and resilience within supply chains create a paradoxical dichotomy. The ability of supply chain managers to navigate and overcome the disruptions caused by this paradox was crucial. By understanding the dynamic interactions between sustainability and resilience, supply chain managers can optimize their decision-making processes to achieve sustainable and resilient supply chains, even during times of disruption. Bellamy et al. identify three types of paradox: the paradoxical dichotomy, where two interacting elements create tensions in the decision space; dilemmas that present short-term trade-offs but tend to resurface; and dialectic contradictions that can become paradoxical when attempting to maintain the core characteristics of the original elements. By recognizing and addressing these paradoxes, supply chain managers can effectively manage disruptions and ensure the long-term success of their supply chains.

In their study, Ivory and Brooks (2018) argued that adopting a paradoxical lens can enhance the ability of the decision-maker to navigate and respond to paradoxical phenomena, thus promoting organizational sustainability and agility. The paradoxical lens allows decision-makers to understand and establish relationships within complex environmental dynamics, enabling them to formulate strategies accordingly. Ivory and Brooks propose that strategic agility fostered through accepting and managing paradoxes enables decision-makers to adapt to the dynamic environment effectively. This strategic agility was characterized by strategic sensitivity, collective commitment, and resource flexibility. This study did not employ paradox theory, as it explicitly examines the contradictory choices made by decision-makers. Paradox theory would be better suited for a quantitative casual study.

Uncertainty Theory

A theory considered for this study was the uncertainty theory. Zadeh (2005) proposed the General Theory of Uncertainty (GTU), which involves modifying reasoning and deduction to account for uncertainty. GTU encompasses most uncertainty theories up to 2005. Liu (2010) introduced a new paradigm of uncertainty theory by integrating elements of probability, credibility, and chance theories. Four axioms define uncertainty theory: normality, monotonicity, self-duality, and countable subadditivity. Memon et al. (2015) and Shen et al. (2019) expanded on Liu's uncertainty theory, focusing on the degree of belief in an event. They introduced constructs such as measuring belief degree, uncertainty variables to measure information uncertainty, and uncertainty distribution on variables. Zeng et al. (2018) developed mathematical factors of belief events affected by epistemic uncertainty, corresponding to Liu's mathematical formulation of uncertainty variables. Gong et al. (2020) and Zhou et al. (2019) argued that cascading disasters cannot be predicted using probability distributions and propose using subject matter experts (SMEs) to provide uncertainty variables. Gong et al. (2020) explained the concept of a frontal disaster event causing cascading events. In Hu et al. (2020) new paradigm, different uncertainty events occurred in phenomena expressed through epistemic uncertainty and probability to avoid confusion for decision-makers. The uncertainty theory and its derivatives offer valuable applications for decision-making in uncertain environments.

In their study, Nilsson et al. (2016) examined the application of probability theory to decision-making judgment. They argue that Costello and Watts's (2014) approach, which combines decision-making judgment with probability theory and heuristic processes, was flawed. Nilsson et al. (2016) suggested that incorporating heuristics into probability theory introduces an element of uncertainty. However, they also acknowledge that heuristics can be valuable in decision-making if two conditions were met: first, heuristic judgments must follow the algorithmic foundations of probability theory, and second, they must result in accurate judgments in real-life situations. Furthermore, the authors provide evidence that, in some instances, heuristic judgment decisions align with the rules of probability theory, particularly in judicial decision-making.

Tang et al. (2020) proposed applying a rough set theory to measure uncertainty. By utilizing rough set theory, Tang et al. can achieve a good approximation of knowledge uncertainty measures. Tang et al. assert that their framework considers existing approaches to uncertainty knowledge measurement and introduces a descriptive framework and an algorithm to enhance the measurement of knowledge uncertainty. This novel approach was promising for improving the researcher’s understanding and quantifying uncertainty in various domains.

In their study, Nishino and Tjahjono (2018) proposed using a game theory framework to analyze product-service systems. The authors argue that this framework serves as a valuable tool for decision-making, providing mathematical inference and strategic direction. Applying game theory to product-service systems establishes an interconnected relationship between customers, competitors, and decision-makers. Within this framework, decision-makers make choices based on their desired outcomes for the players involved. Overall, Nishino and Tjahjono's research contributed to the understanding and applying game theory in product-service systems. This study did not use uncertainty theory because it was more suitable for qualitative decision-making studies. This study did not use uncertainty theory because it was better suited for qualitative decision-making studies.

Complexity Theory (CT)

Complexity theory originated in the mid-1980s from the Santa Fe Institute in New Mexico and has emerged as a significant theoretical framework for understanding real-world phenomena. Mason (2020) defined complexity theory as integrating numerous independent elements that collectively exhibit behavior as a cohesive unit. While complexity theory shares similarities with chaos theory, it was important to note that the two have distinct differences (Deogratias, 2018). Unlike chaos theory, which focuses on elements that do not interact at some level, complexity theory emphasizes the interplay and interaction among multiple elements.

Initially used in physics to explain non-linear events, complexity theory posits that nature was characterized by non-linear, irregular, and asymmetrical systems that defy predictability (Damayanti et al., 2019). Complexity theory was a new paradigm for describing complex phenomena observed in the real world (Kok et al., 2021; Turner & Baker, 2019). An interesting concept within complexity theory was that adaptive systems approach a critical point known as the "edge of chaos," where they were on the verge of collapse (Lowell, 2016).

Complexity theory was a widely discussed topic in the field of research, with scholars offering different perspectives on its scope and impact. Some researchers argue that complexity theory serves as an overarching framework that includes chaos theory, dissipative structures theory, and complex adaptive systems theory (Devereux et al., 2020). Kok et al. (2021) countered this view, stating that complexity theory lacks unifying characteristics. An area of interest within complexity theory was uncertainty theory, which builds upon the idea of multiple pathways leading to the same outcome (Devereux et al., 2020; Prentice, 2020). This perspective challenges the notion of predictability in complex systems. Scholars from CIEAEM Working Group 1 (2019) asserted that complexity theory represents a new paradigm that challenges the limited understanding offered by the Newtonian framework, particularly when studying complex systems. The core premise of complexity theory was that systems were dynamic and constantly evolving, resulting from the interactions of numerous elements (Battistella et al., 2018; Devereux et al., 2020; Lowell, 2016; Mehran & Olya, 2020; Turner & Baker, 2019; Varnali, 2019). This understanding highlights the unpredictable nature of system states. The impacts of globalization have influenced interactions at both micro and macro levels, giving rise to highly dynamic complex systems (CIEAEM Working Group 1, 2019). As a result, complexity theory provides fresh insights into the study of systems, particularly pertinent in the context of the ongoing science-technical revolution (Dziubińska, 2021).

Complexity theory presents an umbrella framework that encompasses various theories and perspectives. While some argue for its unifying nature, others highlight its limitations. Complexity theory offers a paradigm shift from traditional Newtonian understandings and emphasizes the dynamic and unpredictable nature of complex systems, particularly in the context of globalization and the science-technical revolution.

The interconnectedness of economic, social, and political dynamics on a global scale cannot be adequately explained by reductionist paradigms (Devereux et al., 2020; Kok et al., 2021). The complexity of these systems necessitates the development of a new paradigm that considers the diverse interactions and characteristics of complex systems. This new paradigm recognizes complexity as being characterized by connectivity, autonomy, emergence, nonequilibrium, nonlinearity, self-organization, and co-evolution (Rzevski et al., 2018). These key features highlight complex systems' intricate and unpredictable nature, where small changes can have significant effects, and the system continually adapts and evolves in response to its environment. Deterministic models were insufficient for comprehending such complexity, requiring a shift towards a more comprehensive approach to understanding and addressing complex interactions within systems (Devereux et al., 2020; Kok et al., 202).

The CIEAEM Working Group 1 (2019) proposed that complex systems exhibit accelerated dynamics, highly sensitive to small perturbations that may lead to substantial impacts. Turner and Baker (2019) argued that complexity theory can be applied to understand adaptive innovation, especially in the context of technological advancements and globalization. Complexity theory was characterized by non-linear dynamics, chaotic behavior, adaptability, emergent phenomena, self-organization, and the absence of central control (Eppel & Rhodes, 2018; Gligor et al., 2022; Oakden et al., 2021; Walton, 2016).

Mason (2020) identified four key elements of complexity theory: nonlinearity, which makes predicting successful actions difficult; spontaneous self-organization, where elements align and adapt to each other; adaptability, allowing the system to adjust for overall benefit; and the absence of control oversight, with competition and cooperation governing outcomes. Mason also highlights that minor events can have significant consequences due to chain reactions and the potential for system-wide effects. It was important to note that complexity theory focuses on the micro-interactions of the components comprising a phenomenon, while chaos theory examines macro interactions in complex systems. Consequently, complexity theory was not used in this study, as it focuses on understanding a singular phenomenon and its constituent parts.

Uncertainty Management Theory (UMT)

Brashers' (2001) work established the development of uncertainty management theory (UMT). This theory provides a framework for understanding how uncertain environments influence management. In such environments, managers tend to withdraw and make decisions based on what makes them comfortable. Uncertainty management theory aims to understand individuals' responses to uncertainty and their strategies for seeking information. Brashers highlights two key principles of uncertainty management theory. First, emotions play a significant role in people's responses to uncertainty, surpassing the anxiety typically associated with such situations. Second, information seeking can take different forms: positive, negative, neutral, or a combination. Brashers also explores how individuals acquire information to make cognitive decisions in uncertain circumstances. Brashers' research has contributed to the development of UMT, providing valuable insights into how individuals and managers navigate uncertain environments and effectively manage uncertainty through emotions and information-seeking strategies.

Alvarez et al. (2018) introduced a paradigm integrating uncertainty management theory (UMT) into organizational and management constructs. As presented by Alvarez et al., the Knightian uncertainty premise distinguishes between risk and uncertainty. Risk refers to situations where decision-makers know the possible outcomes but do not know the precise outcome. In contrast, uncertainty refers to situations where decision-makers lack knowledge of the probability and specific outcomes.

Initially, it was widely believed that uncertainty did not significantly impact decision-making because decision-makers could always rely on probability distributions when making choices. In 2016, the concept of uncertainty began to gain prominence. Several factors drove this shift in perspective. First, real decision-makers often rely on heuristics and biases derived from uncertain conditions rather than risk. This highlights the influence of uncertainty on decision-making processes. Second, it became clear that not all choices were made in high-risk situations but in ambiguous ones. This realization challenged the assumption that decision-makers always have access to probability distributions. Lastly, globalization has created an uncertain environment for managers, where traditional notions of probability and decision-making may no longer be applicable. Managers now face complex and unpredictable dynamics that require a different understanding and approach. Alvarez et al. shed light on the importance of uncertainty in decision-making processes, challenging the prevailing belief that decisions were based solely on risk. The emergence of uncertainty as a crucial factor in decision-making can be attributed to the application of heuristics and biases, the recognition that not all decisions were made at risk, and the uncertain environment created by globalization.

Rains and Tukachinsky (2015) proposed the Uncertainty Management Theory (UMT) as a framework to understand how individuals cope with uncertainty. UMT emphasizes the appraisal of uncertainty in terms of its meaning rather than simply as positive or negative. A key aspect of UMT was information management, which was crucial in how individuals search for information to cope with uncertainty. Rains and Tukachinsky argued that UMT can predict behaviors related to uncertainty management, such as information avoidance. They suggested that information avoidance was a unique coping mechanism that allowed people to maintain hope, deny uncertainty, avoid overexposure, and refrain from action. According to Rains and Tukachinsky, UMT offers benefits by enabling individuals to manage uncertainty using information effectively. They assert that investing in information search directly affects uncertainty management and decision-making success. Rains and Tukachinsky acknowledged that not all information searches successfully manage uncertainty. It was important to note that obtaining more information does not guarantee complete certainty and was not a cure-all for uncertainty. Although UMT was not used in the study discussed, the authors suggest it was better suited for qualitative studies of decision-making.

Uncertainty Shock

Uncertainty shocks were events that have the potential to disrupt economies and financial markets, resulting in adverse effects. These shocks can arise from various sources, such as political instability, natural disasters, or unexpected changes in government policies. The impacts of uncertainty shocks can vary in magnitude and duration. Major uncertainty shocks were particularly concerning because of their unpredictable nature. These shocks often catch markets off guard, leading to increased volatility and a significant negative impact on economic growth. The lack of foresight and preparedness for such shocks makes countering challenging.

On the other hand, there were also mild uncertainty shocks that were more easily predictable and could be countered with appropriate measures. These shocks may arise from anticipated events like scheduled elections or policy announcements. In these cases, market participants can take pre-emptive actions to mitigate the potential adverse effects by adjusting their investment strategies or hedging their positions. Although mild uncertainty shocks can be managed easily, major uncertainty shocks pose a greater challenge due to their unpredictable nature. Policymakers, businesses, and individuals must recognize the importance of building resilience and implementing robust risk management strategies to navigate uncertain times.

In their study, Hurley-Hanson and Giannantonio (2009) surveyed executives from various companies to gather information on crisis response plans, crisis communication plans, succession plans, and technology. They found that many organizations were ill-prepared for major uncertainty shocks between 2001 and 2005. These shocks included the 9/11 terrorist attacks, the Indian Ocean tsunami in 2004, and Hurricane Katrina in 2005. The authors highlight that existing crisis response plans were inadequate in dealing with these uncertainty shocks. Although they had plans, the organizations had not exercised or considered the unpredictability of such shocks. This oversight led to significant consequences, including loss of life, economic impacts, and destruction of infrastructure. Hurley-Hanson and Giannantonio note that the knowledge and influencers learned from 9/11 were either forgotten or misused during subsequent uncertainty shocks.

Hurley-Hanson and Giannantonio highlight the need for adaptable crisis response plans to address the uniqueness and unpredictability of such events.

The United States World Trade Towers Attack on September 11, 2001 (9/11)

In their study, Gaibulloev and Sandler (2019) examine the impact of the 9/11 terrorist attack on the US World Trade Towers and its economic effects. They argue that, at the macro level, terrorist attacks do not significantly affect economic growth and GDP. However, they acknowledge that at the micro-level, terrorism can influence tourism and foreign investments, although these effects were transient, and recovery was swift. The authors also discuss the global reactions to 9/11, which led to significant changes in the global security landscape. The United States, in particular, implemented measures such as trading civil freedoms for security, experiencing large-scale global stock losses, and reallocating resources toward counterterrorism operations. The creation of the Department of Homeland Security was a direct response to these events, aimed at coordinating efforts and resources across various government departments to protect the country. During the past 50 years, Gaibulloev and Sandler (2019) noted that terrorism has undergone fundamental changes. Transnational terrorist incidents have decreased by 40%, while domestic terrorism incidents have followed a similar pattern. Post-9/11, terrorist activities have shifted to the Middle East, Africa, and South Asia, and religious fundamentalist groups have established long-term survival strategies.

Contrary to popular belief, Gaibulloev and Sandler (2019) argued that facilitators of terrorism, such as globalization, poverty, and democracy, do not have a direct relationship with terrorism. Their research shows that there was no relationship between terrorism and globalization, no relationship between poverty and terrorism, a nonlinear relationship between GDP and terrorism, and no relationship between democracies and terrorism. Gaibulloev and Sandler (2019) provided valuable insights into the economic impact of terrorist attacks, the global reactions to such events, and the changing nature of terrorism. Their research challenges commonly held assumptions about the facilitators of terrorism and contributes to a better understanding of this complex phenomenon.

According to Sojung (2018), empirical evidence suggests investors reacted excessively to the 9/11 terrorist event. On the first day of trading, there were significant negative returns, indicating an overreaction by investors and resulting in a substantial negative abnormal return. Sojung's research indicates that it was not the investors who initiated the negativity but the analysts who acted as the catalysts.

The uncertainty surrounding the aftermath of 9/11 played a significant role in this overreaction. Questions regarding the possibility of further attacks, the closure of US airspace, the executive branch's role in handling the situation, and the anticipated US response contributed to the heightened sense of uncertainty. Although the 9/11 attack was limited to the United States, it served as a short-lived shock with a high global impact. Because of the 9/11 incident, the military and a national command policy centered on the "War on Global Terrorism" stood up. This answer underscores the seriousness of the issue and the need for an all-encompassing plan to counteract the worldwide threat of terrorism.

COVID-19 as an Uncertainty Shock

The COVID-19 pandemic has significantly impacted the world and put enterprises in financial hardship (Amnim et al., 2021). Without government intervention to mitigate the effects, economic failure could extend beyond businesses, resulting in a loss of confidence and potential dissolution of governments. According to Elenev et al. (2020), the United States Government has already authorized bailouts totaling $2.3 trillion, while the government budget in 2019 amounted to $4.4 trillion. It was assumed that the US Government would continue to allocate funds for economic recovery efforts in the near future.

The COVID-19 pandemic has profoundly impacted the global economy, causing unprecedented uncertainty (O'Sullivan et al., 2020). Despite governments having contingency plans, the swift and uncontrollable spread of the virus in a globally interconnected world made it difficult to prevent the pandemic without extreme measures against its epicenter, China. As a result, numerous markets collapsed, businesses failed, and countries isolated themselves (Elenev et al., 2020). The COVID-19 pandemic has led to a significant contraction in all aspects of the economy, including credit lines, reserves, job layoffs and furloughs, and business insolvencies (Shapira et al., 2021). Studies have shown that the uncertainty shock caused by COVID-19 can persist for years, even with government subsidies. In particular, the airline industry has been severely affected, with a 60-80% decrease in capacity due to the constraints imposed to curb the spread of the virus (Sobieralski, 2020). Given the unpredictability and magnitude of the COVID-19 uncertainty shock, it was crucial to understand the behavior of individual investors in response to the pandemic. Research by Giglio et al. (2020) provides valuable information on investment decisions made by individuals before, during, and after the market crash caused by the COVID-19 pandemic.

In their study, Goolsbee and Cyverson (2020) examined the factors contributing to the economic decline caused by the COVID-19 pandemic. They argue that the collapse of economic activity can be attributed to the impact of the virus on consumer preferences for purchases. Through the analysis of cell phone records from 2.5 million businesses across various industries, the authors shed light on consumer behaviors during this period. Based on their findings, Goolsbee and Cyverson presented empirical evidence indicating that reports of COVID-19 deaths significantly influenced consumer shopping patterns. They suggest that fear of death prompted consumers to shift their preference from larger, busier businesses to smaller, less crowded ones within the same industry. The authors demonstrate that consumer traffic declined by 60 percentage points, with government lockdown and stay-at-home orders accounting for only seven percentage points of this decrease. The government-imposed lockdown measures shifted consumer behavior from non-essential establishments like restaurants to essential businesses like food stores. The investigation of Goolsbee and Cyverson also provided insight into the impact of the lockdown on employment, with a 60% decrease in employment attributed to social distancing policies.

Giglio et al. (2020) examined investors' beliefs during three time periods of the COVID-19 pandemic: before, during, and after the market fluctuations. They found that before the market peak in mid-February 2020, the average belief of investors led to the inference that over three years, the stock market would continue to show reductions, and the GDP would decline, albeit at a slower rate. During the market decline in mid-March 2020, investors believed there would be a short-term stock market decline of 30% and a corresponding % GDP decline of 3%. After the market rallied in mid-April but remained 17% lower than the peak, long-term investor respondents believed that the stock market return and GDP would grow and remain stable for ten years. These findings suggest that investors' beliefs varied depending on the timing of the pandemic and its impact on the market, with different expectations for short- and long-term results.

According to Donthu and Gustafsson (2020), the long-term effects of the COVID-19 pandemic were challenging to predict. They argue that individuals and companies will reduce investment and increase savings, decreasing economic growth. The pandemic has accelerated business closures and disrupted commerce in various sectors, particularly the service industry. Businesses have hindered recovery efforts by prioritizing tasks, optimizing spending, and implementing hiring freezes. The travel industry has been hit hard, with 80% of hotel rooms remaining empty and airlines cutting their workforce by 90%. The impact of the pandemic extends to all sectors of business, people, and government (O’Sullivan et al., 2020). Not all business domains, such as online communications, entertainment, shopping, and corporate social responsibility, have been negatively affected. It was important to note that accurate projections were challenging to formulate due to the ongoing pandemic.

Intelligent Analytics

IA plays a crucial role in shaping strategic outcomes for decision-makers. IA, also known as artificial intelligence and big data analytics, has become a national imperative in many countries (Manikam et al., 2019). According to Bhargava et al. (2016), intelligent agents were software algorithms that enabled real-time predictive data analysis of dataspheres. Faster access to data is essential for businesses (Ajah & Nweke, 2019), as it allows four key output pillars: descriptive knowledge, diagnostic understanding, predictive analysis, and perceptual influence on future events. IA uses statistical techniques, data mining, and algorithms to generate probabilistic outcomes from dataspheres. Intelligent agents extract usable information by exploring databases to form predictive insights (Bhargava et al., 2016). IA can handle the tedious and repetitive data mining task, thus improving decision-making processes for strategic outcomes. It also adapts multisource information, triangulating data for predictive analysis (Bhargava et al., 2016). In complex environments, IA navigates uncertainty and relies on judgments to generate positive predictions (Agrawal et al., 2018).

According to Anagnostopoulos et al. (2016), the growth and development of AI technologies have led to global interconnection. They argue that the big datasphere was experiencing exponential growth due to cheaper digital interface systems and the availability of more relevant data for researchers. Advances in technology, such as heterogeneous information systems, social networks, the Internet of Things (IoT), and data capture technologies, generate structured and unstructured data (Azard et al., 2020). AI has significantly transformed data delivery and manipulation. Unstructured data now account for approximately 90% of the datasphere, and the implementation of AI has enabled scalable data storage, distributed analysis, real-time processing, and visualization.

Baesens et al. (2016) argued that the emergence of big data and artificial intelligence (AI) profoundly transformed the business landscape. They define big data using the four Vs: volume, velocity, variety, and veracity. These four dimensions present new opportunities for decision-making and enable organizations to adopt a data-driven approach in executive decision-making processes. By leveraging actionable intelligence derived from big data analytics, businesses can develop strategies to gain a competitive advantage, especially in uncertain events. Baesens et al. emphasized that big data analytics extend beyond advanced data reporting, allowing organizations to derive meaningful insights from the data. They further contend that big data analytics enable the identification of causal relationships between variables, thereby facilitating the prediction of outcomes and generating actionable intelligence. It was essential to acknowledge the global interconnectedness between businesses and individuals, as it significantly influences economic conditions on a global scale.

Big data analytics were pivotal in transforming organizations and reshaping decision-making processes in today's rapidly evolving business landscape. Baesens et al. highlighted critical issues that can hinder the successful implementation of big data analytics. One major challenge was the quality of the data. Businesses must recognize the importance of investing in data quality to ensure the reliability and accuracy of the information being analyzed. Many companies consider such investments expensive and daunting, leading to stagnation in implementing big data analytics, a failure to take advantage of valuable insights, and a missed opportunity to harness actionable intelligence. Ethical concerns also arise when dealing with the vast amount of personal information within the big data datasphere. To overcome these concerns, new ethical paradigms must be developed, ensuring that the privacy and rights of individuals were respected while leveraging the potential of big data analytics. Despite these challenges, the benefits of implementing big data analytics for business decision-making were substantial. Using big data allows organizations to gain actionable intelligence previously unattainable through traditional data analytics approaches. By leveraging the power of big data, businesses can optimize their processes, rebalance decision-making relationships, and significantly improve their overall operations.

Supply Chain Resiliency

In today's global business landscape, supply chains play a vital role in driving competition, supporting the global economy, and laying the foundation for business growth (Adobor, 2019; Karl et al., 2018). Supply chain managers were confronted with numerous disruptions that posed significant risks to the smooth functioning of supply chains. These disruptions include design vulnerabilities, operations disruptions, reduction in the number of providers, natural and man-made disasters, shortage of skilled personnel, the impact of globalization, negative publicity from news organizations, and political upheavals (Cardoso et al., 2015; Chen et al., 2020; Hosseini et al., 2019, 2020; Ribeiro & Barbosa-Povoa, 2018). Resilient supply chains have gained considerable attention to combat these risks. Resilience refers to the ability of the supply chain to effectively respond to disruptions and quickly stabilize before moving towards recovery (Adobor & McMullen, 2018; Agigi et al., 2016; Cheng & Lu, 2017). Supply chain resiliency involves proactively identifying risks, developing mitigation strategies, and implementing contingency plans to reduce the impact of disruptions on SC operations (Ganesh & Kalpana, 2022). The importance of building resilient supply chains cannot be overstated. By adopting a resilient approach, business leaders can effectively assess risks, develop appropriate strategies, and enhance the organization's ability to withstand and recover from disruptions. Adopting a resilient approach not only safeguards the continuity of operations but also enhances the overall competitive advantage of the business in the marketplace (Bak et al., 2020).

The literature presents varying perspectives on whether risk management can effectively mitigate vulnerability caused by disruptions in global supply chain interactions. Scholars such as Ali et al. (2021), Kochan and Nowicki (2018), C. Singh et al. (2019), and Wong et al. (2020) argued that risk management alone may not fully address the risks and uncertainties associated with global supply chains. Sáenz et al. (2018), Y. Li et al. (2021), Goldbeck et al. (2020), and Jafarnejad et al. (2019) emphasized that implementing risk management practices can enhance SCR. They suggest that understanding the dynamics of disruptions enables managers to implement risk management to foster resilience effectively. They argued that the risk management process was more accessible and easier to implement during the early stages of supply chain development.

According to recent research (Ali et al., 2021), implementing new paradigms was crucial to protect supply chains from disruptions. Supply managers in all business domains play a vital role in developing sustainable supply chains by formulating solutions based on the probability of disruptions (Behzadi et al., 2020; Goldbeck et al., 2020; Jafarnejad et al., 2019; Ribeiro & Barbosa-Povoa, 2018; Scholten et al., 2019). To effectively combat supply chain disruptions, managers must build tangible and intangible capabilities (Chowdhury et al., 2019; Ivanov, 2018). Business leaders must also reconsider the reliance on globalization, outsourcing, and just-in-time supply chains, as these practices can make supply chains more vulnerable to disruptions (Cardoso et al., 2015). IA can provide a competitive advantage in this regard. Given the complexity of global supply chains, analyzing large amounts of data and using metrics formed through IA was crucial for business leaders to make informed and proactive decisions to overcome disruptions (Ribeiro & Barbosa-Povoa, 2018). Furthermore, the ability of supply chain development to self-correct was identified as a potential solution to counter supply chain disruptions (Bak et al., 2020). SCR was a dynamic capability that allows adaptability to disruptions (Wong et al., 2020). Developing SCR is a strategic capability that positions businesses for competitive advantage (Scholten et al., 2020). Lastly, investment in disruption prevention was recommended for business managers (Li et al., 2021).

Radom effect meta-analysis

In scientific research, new studies continue contributing to our understanding of various phenomena. Simply relying on individual studies may not provide a comprehensive overview. A random effect meta-analysis can be described as a study of studies. It systematically synthesizes information from multiple sources for a more robust and reliable analysis. Combining data from various studies allows a random effect meta-analysis to achieve a larger sample size, resulting in increased statistical power. Several key principles guide the process of conducting a random effect meta-analysis. First, it was essential to approach the task systematically. Requires following a predetermined set of criteria for selecting relevant studies, ensuring a rigorous and objective approach. Second, a random effect meta-analysis focuses on the results obtained from multiple data sets. This comprehensive approach allows for a more nuanced understanding of the phenomenon under investigation, as it considers the variability across different studies. Lastly, a random effect meta-analysis is a quantitative analysis. Radom effect meta-analysis relies on statistical methods to analyze and interpret the data. A random effect meta-analysis provides a clear and objective assessment of the overall findings by quantifying the results.

In recent research, Allen (2020) suggested that random effect meta-analysis was a versatile family of techniques that allowed researchers to synthesize large data sets. Radom effect meta-analysis provides a valuable tool for parsing and analyzing large data sets, allowing researchers to estimate relationships and average the effects of investigations in a phenomenon (Allen, 2020). Graziani and Venturini (2020) propose an application for multiple discrete outcomes through a multiple-outcome network random effect meta-analysis framework. They argue that this approach allows for a stronger correlation across multiple outcomes, particularly when measuring results from multiple studies on one event. The outcomes become nested within this framework, providing a more robust analysis (Graziani & Venturini, 2020). Moeyaert (2019) highlights the importance of multilevel random effect meta-analysis as a synthesis technique for quantitatively integrating ESs across studies. This method establishes a paradigm for forming an evidence-based research process and offers a logical and reliable statistical approach across studies. Moeyaert's study validated the statistical properties of multilevel random effect meta-analysis through repeatable Monte Carlo simulation studies (Moeyaert, 2019). Random effect meta-analysis is a valuable tool for researchers to synthesize and analyze large data sets, estimate relationships, and average the effects of investigations. Multiple outcome networks and multilevel meta-analyses improve the analysis and provide robust statistical approaches for evidence-based research (Allen, 2020; Graziani & Venturini, 2020; Moeyaert, 2019).

Radom effect meta-analysis was a valuable statistical tool for assessing the significance of predictor and dependent variables across multiple studies (Paul & Criado, 2020). It allows researchers to identify common trends and draw meaningful conclusions. To conduct a random effect meta-analysis, specific inclusion criteria that include clear operational definitions of predictor and dependent variables, a description of the study population, and details of the research design, such as randomization, sample size, and time period (Cooper, 2020), additional statistical elements, such as ES measures, median data, excess significance results, and the R-index measure, can enhance the reliability of a random effect meta-analysis (Kossmeier et al., 2020). Despite its many strengths, random effect meta-analysis also has limitations, including the need for certain assumptions, the potential for publication bias, and the requirement for researchers to have a solid understanding of statistical methodologies (Allen, 2020; Graziani & Venturini, 2020; Moeyaert, 2019).

Rouder et al. (2019) proposed a novel approach to random effect meta-analysis, shifting the focus from overall mean trends to examining the plausibility of effects in the same direction. They argue that ordinal properties, such as the status of effects as positive, neutral, or negative, should be considered in all studies rather than relying solely on metric-based analysis. One of the key advantages of this approach was that it allows a better understanding of the relationships and causality between predictor and dependent variables. Radom effect meta-analysis can uncover a more accurate and reliable dataset, leading to a more factual representation of the truth between studies using ordinal properties.

Rouder et al. acknowledged several limitations. First, the requirement for the studies to have the same dependent variable restricts the scope of analysis. Furthermore, not all comparisons may be acceptable, and there was a potential for misleading interpretations. Lastly, there were instances where the available data may not provide sufficient evidence to draw conclusive findings.

Transition

Section 1 of the research paper provides a comprehensive foundation for the chosen research topic, including background information and the identified business problem. The research method and design were justified within this section, considering the problem, purpose, nature, and research question. A random effect meta-analysis approach was used to strategize the study, with the understanding that the random effect meta-analysis population was equivalent to the literature. Additionally, Section 1 incorporates the theoretical framework of chaos theory, which aligns with the characteristics of the COVID and IA systems. The potential benefits for businesses and the impact on social change were also discussed. A comprehensive review of the existing literature was presented, including discussions on chaos theory, other relevant theories, COVID, IA systems, SCR, and random effect meta-analysis.

Section 2 restates the problem and purpose statement and serves as the foundation for the study outline. This section covers various topics, such as the role of the researcher, participant selection, research design, population and sampling, ethical considerations, data collection instruments and techniques, data analysis, and study validity. A smooth transition was made from Section 2 to Section 3.

Section 3 focuses on the research itself and begins with a restatement of the purpose of the study and a summary of the findings. The section includes the presentation of the findings, their applicability to professional business practices, inferences for social change, suggestions for action, suggestions for further research, reflections on the researcher's experience, a conclusion, and appendices.

Section 2: The Project

Section 2 contains a restated problem and a purpose statement as the foundation for the outline of the study. The discussion in Section 2 contains the topics of (a) role of the researcher, (b) participants, (c) research and design, (d) population and sampling, (e) ethical research, (f) data collection instrument, (g) data collection technique, (h) data analysis, and (i) validity of the study. In general, Section 2 provides a comprehensive overview of various key aspects of the study, establishing a solid foundation for the research and addressing the research problem and the purpose.

Purpose Statement

The purpose of this quantitative correlation study was to examine the relationships of COVID on SCR and IA on SCR. The predictor variables were COVID and IA. The dependent variable was SCR. There was no population for this study as this study was a random effect meta-analysis of the existing literature. The geographical location of this study was irrelevant.

Role of the Researcher

The role of the researcher in this quantitative correlation random effect meta-analysis study was that of a data collector. As a data collector, the researcher serves as an instrument of data collection (Wa-Mbaleka, 2020). Smith et al. (2021) further delineated the researcher’s role as (a) setting criteria and keywords to identify relevant studies, (b) determining which studies were included in the analysis, (c) observing the phenomena from an external standpoint, and (d) testing data through hypotheses using statistical techniques for analysis. The researcher’s primary responsibility was to collect information that effectively addresses the research questions. In addition, the researcher serves as an objective observer of the phenomenon under investigation.

This study has significant implications for various sectors of business and society. As both a consumer of products and a researcher, I am familiar with the variables examined in this study. My educational background in engineering and national resourcing provides me with the necessary knowledge to conduct statistical research for quantitative correlational random effect meta-analysis.

Regarding ethical considerations, the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research (1979) the Belmont Report established by the Department of Health, Education and Welfare outlines guidelines and principles for the ethical use of human subjects in research, including respect for persons, beneficence, and justice. Although my study does not involve direct interaction with human participants, I am well-versed in the ethical principles outlined in the Belmont Report. I will ensure that they are upheld throughout the research process.

Participants

This study focuses on performing a random effect meta-analysis of existing literature to determine whether there was a correlation between the predictor and the dependent variables. It was important to note that no human participants were involved in this study. The primary objective was to analyze the available data from various sources and assess whether a relationship exists. The original authors of the studies included in the random effect meta-analysis have ensured that any identifiable information of the participants has been removed. This study expanded the current understanding of the subject matter by conducting a correlational statistical analysis.

Research Method and Design

In social science research, quantitative and qualitative approaches are two common methods used to investigate phenomena (Lo et al., 2020). The choice between these methods depends on the researcher's chosen framework. Quantitative research involves converting data into numerical information and analyzing it using statistical techniques (Basias & Pollalis, 2018). This method allows for identifying patterns, trends, and relationships among variables. It relies on collecting structured data through surveys, experiments, or existing data sets.

Qualitative research focuses on generating data based on the lived experiences of the study participants (Saunders et al., 2019). This method involves collecting data through interviews, observations, or the analysis of textual materials. Qualitative research aims to provide a deep understanding of social phenomena by exploring the perspectives, meanings, and contexts of the individuals involved.

Research Method

I have chosen to employ a quantitative research method for my study. Bridgmon and Martin (2012) stated that quantitative research involves measuring variable change through empirical techniques. This method allows for the statistical testing of variables, as Basias and Pollalis (2018) and Almalki (2016) suggested.

Quantitative research offers several advantages. Firstly, it reduces the biases that may arise from personal feelings when observing a phenomenon. Additionally, it allows the synthesizing of large datasets and facilitates the comparison of numeric data. Moreover, quantitative data analysis was repeatable, ensuring reliability (Basias & Pollalis, 2018). The researcher can control variables and standardized instruments, as Rutberg and Bouikidis (2018) and Watts et al. (2017) emphasized. It is important to note that the researcher's actions do not influence the phenomenon observed in quantitative research (Kang & Evans, 2020). Instead, the researcher observes the phenomenon and establishes statistical relationships between the variables (Ramlo, 2020).

Although qualitative methods, as demonstrated by Bell and Wilmott (2017), interpret textual and interview data to understand individuals' experiences, they were inappropriate for this study. Using a quantitative method allows statistical measurement of relationships between variables rather than relying on subjective interpretations of lived experiences (Saunders et al., 2019).

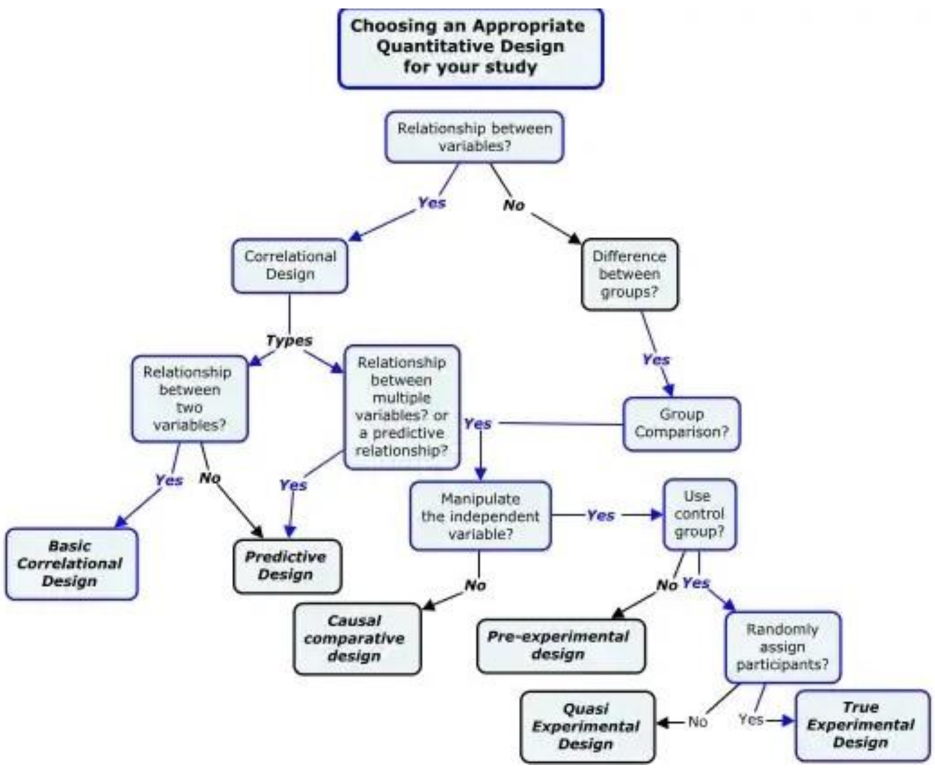
A mixed-method research approach, which combines quantitative and qualitative aspects, was unsuitable for this study because the study lacks the interpretation of individual experiences essential to understanding the phenomenon (Kansteiner & König, 2020). Using a quantitative research method was appropriate for my study, as it allows for the measurement and statistical analysis of variable change, ensuring objective and reliable findings.

Research Design

Research design plays a pivotal role in the research process, as it is the most crucial decision a researcher makes (Abutabenjeh & Jaradat, 2018). Research design is the fundamental process of investigating a phenomenon (Abu-Taieh et al., 2020). In the context of quantitative research, Bloomfield and Fisher (2019) and Creswell and Creswell (2020) identify three main designs: correlation, quasi-experimental, and experimental. A decision tree developed by Adu (2015), Figure 1, can be used as a guide to select the appropriate quantitative design.

Figure 1

Decision Tree for Choosing a Quantitative Design



Note: From "Very simple way of choosing an appropriate quantitative research design for your study", by P. Adu, 2015, *SlideShare*, https://www.slideshare.net/kontorphilip/very-simple-way-of-choosing-an-appropriate-quantitative-research-design-for-your-study. See Appendix A for permission to use.

Experiential design is often called a true experiment with a scientific method to establish cause-effects (Rutgers Libraries, 2021). The experimental design uses control groups and randomization to form a statistical analysis of a phenomenon (Chih-Pei & Chang, 2017). The researcher uses experimental design estimates to form a causal impact of a change in predictor variables, which causes a change in the dependent variable (Saunders et al., 2019). An experimental design was unsuitable for this study, as the focus was not to seek cause and effect.

Experiential design, also known as a true experiment, was commonly employed in research to establish cause-and-effect relationships using a scientific method (Rutgers Libraries, 2021). This design uses control groups and randomization to facilitate statistical analysis and draw conclusions about a phenomenon (Chih-Pei & Chang, 2017). Researchers can manipulate predictor variables to determine their causal impact on dependent variables (Saunders et al., 2019). An experimental design was not appropriate because the purpose of the study was not to seek cause and effect.

A quasi-experimental design is a research approach that involves studying a single sample without a control group selected by the sample population (Maciejewski, 2020). This design establishes cause-effect relationships between variables without manipulating them (Rutgers Libraries, 2021). Researchers use quasi-experimental designs to estimate the causal impact of changes in predictor variables on the dependent variable (Saunders et al., 2019). In this study, a quasi-experimental design was inappropriate, as the objective was not to establish cause-and-effect relationships.

The research design for this study was correlational. Correlational designs determine predictions and relationships among variables (Seeram, 2019). Correlational designs employ statistical measurements to assess the strength of relationships (Mat Roni et al., 2020; Moeyaert, 2019). Correlational designs allow researchers to analyze evidence across studies and identify commonalities (Gurevitch et al., 2018). By investigating the association between predictor and dependent variables, correlation designs empirically determine the degree of association between them (Queirós et al., 2017). This design was suitable for this study, as it aims to assess relationships, make predictions, and use secondary data for variables such as COVID, IA, and SCR (Burkholder et al., 2019).

Population and Sampling

Van Hoek (2020) provided (a) that a population was a distinct unit under exploration and (b) that a sample was a subset of the population. The population of this study consisted of articles focusing on supply chains. The study range was from December 2019 to December 2023. The scope of the articles was on data from studies that have COVID (predictor variable), IA (predictor variable), and SCR (dependent variable) that cover a combination of at least one predictor variable and the dependent variable. The sample for this study was a subset of articles from the population that met the selection criteria.

According to Van Hoek (2020), a population refers to a distinct unit under exploration, while a sample is a subset of the population. For this study, the population consisted of articles focusing on SCR. The study period was from January 2020 to

December 2023. The scope of the articles included in this study specifically focused on data from studies that examine the relationship of COVID on SCR and IA on SCR. The inclusion criteria for the articles required a combination of at least one predictor variable (COVID or IA) and the dependent variable (SCR). The sample for this study was a subset of articles from the population that met the selection criteria. By selecting articles within this scope, the study aims to provide valuable insights into the relationship of COVID on SCR and IA on SCR in supply chain management.

Ethical Research

As an independent researcher, I understand the importance of ethical considerations when conducting research. In this study, no human subjects were involved. The original author sanitized participant identification data from their studies to ensure privacy and confidentiality of any data used in this random effect meta-analysis. Therefore, there were no apparent ethical concerns regarding the participants in this study. It was worth noting that Walden University has a strict policy that requires researchers to obtain institutional review board (IRB) approval before proceeding with any research involving human subjects. In this case, the IRB approval number for the study was 1014273, which was received on 11-23-2022. This adherence to ethical guidelines and the IRB approval further solidifies the study's credibility and reliability.

Data Collection Instrument

The data collection instrument for this study involves conducting a literature review using secondary data on supply chains. A comprehensive database search included articles for random effect meta-analysis (Harari et al., 2020). Multiple databases were used, such as IEEE, Emerald Insights, Google Scholar, Science Direct, Applied Science, Elsevier, Taylor & Francis, ResearchGate, Wiley, Springer, Bureau of Economic Analysis, Walden University Library, Federal Reserve, International Monetary Fund, and National Bureau of Economic Research. Search criteria focus on predictor variables and the dependent variable.

After the initial search, a secondary review was performed to identify relevant articles for inclusion in the study (Pigott & Polanin, 2020). A random effect meta-analysis design analyzes evidence across studies and establishes commonalities (Gurevitch et al., 2018). Only studies that meet the random effect meta-analysis acceptance criteria were included, allowing for the determination of correlation and ES (Moeyaert, 2019). Radom effect meta-analysis was valuable in consolidating and quantifying large, complex, and conflicting literature (Fokkens, 2019).

Considerations such as sample size, scale of measurement, and statistical power relationships ensure a meaningful statistical inference to the null hypothesis (Faul et al., 2009). Radom effect meta-analysis allows the researcher to form statistical inferences through the literature. By employing a random effect meta-analysis of existing data from other studies, this research approach was the most suitable and effective instrument for this study.

Nature of Scale of Variables

The development of appropriate measurement scales was a critical decision for researchers. The implications of selecting an incorrect measurement scale can harm one's reputation and expertise (Francis et al., 1999). Using the wrong scale can lead to biased conclusions and misinterpretation of data, leading to false findings (Saunders et al., 2019). Measurement scales were central to quantitative research (Merom & John, 2018; Prasad, 2017). Understanding the different data types was crucial, as it can be continuous (taking any value) or discrete (measured precisely). Researchers measure data using variables that connect empirical observations with mathematical expressions (Prasad, 2017). The four commonly recognized measurement scales are ordinal, nominal, interval, and ratio (Saunders et al., 2019).

In my study, I used specific scales of measurement and corresponding metrics. I used the interval scale and metrics such as disruption effects and recovery challenges for the COVID measurement scale. I used the nominal scale for the IA measurement scale and considered metrics such as Big Data, IoT, and Bitcoin. Lastly, I used the nominal scale for the supply chain resiliency scale of measurement and incorporated metrics such as agility, flexibility, visibility, robustness, responsiveness, organizational performance, and resilience. By carefully selecting and applying the appropriate measurement scales and metrics in my study, I contributed to advancing knowledge in my research field.

A common approach to validate a random effect meta-analysis was to test homogeneity, as Cooper (2020) mentioned. However, before testing homogeneity, assessing heterogeneity was essential (Lin, 2017). Two statistical methods commonly used were Cochran 's-Q test and I^2 (Saunders et al., 2019). These tests provide valuable information on the presence of heterogeneity in the data.

Data Collection Technique

The research question for this study was, “To what extent, if any, is there a relationship of COVID on SCR and IA on SCR?” To answer the question, I used a random effect meta-analysis step process derived from Paracha et al. (2017) (a) from the research question, (b) search databases, (c) search criteria, (d) collect data, (e) statistical analysis, and (f) report analysis.

The research question for this study aims to investigate the potential relationship of COVID, IA, and SCR. A random effect meta-analysis approach will address this question, following a step process outlined by Paracha et al. (2017). This process involves (a) formulating the research question, (b) performing a comprehensive search of relevant databases, (c) establishing specific criteria for the selection of studies to be included, (d) collecting data from the selected studies, (e) performing statistical analysis to examine the relationship between the variables of interest, and (f) reporting the results of the analysis.

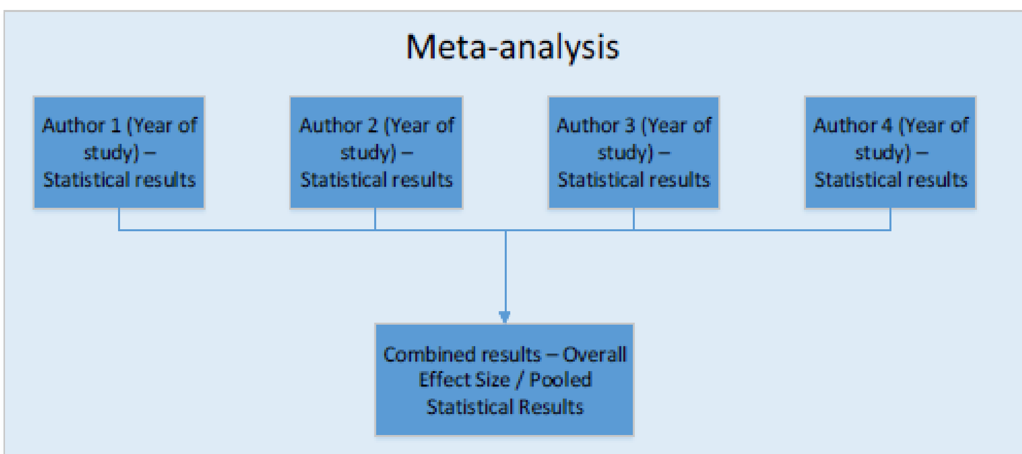
Using this systematic and rigorous approach, I aimed to provide insight into the impact of COVID on SCR and IA on SCR. This research aims to improve current knowledge on SCR and offer practical insight for practitioners and policymakers in addressing the difficulties brought about by the COVID-19 outbreak.

Radom effect meta-analysis

The researcher employs a random effect meta-analysis technique to address the research question and test the hypothesis. Radom effect meta-analysis was a powerful tool to advance scientific research by quantifying existing knowledge and uncovering areas that require further investigation (Gurevitch et al., 2018). By conducting a random effect meta-analysis, the researcher systematically analyzes empirical evidence to support or refute the hypothesis (Havránek et al., 2020). This statistical approach allows for synthesizing findings from multiple studies by identifying commonalities across diverse fields of study and methodologies (Gurevitch et al., 2018). Figure 2 visually represents combining studies, showing how information from selected studies was integrated to form a larger sample population and provide statistical data inputs for the research study (Polanin et al., 2017). This simplistic diagram illustrates the straightforward process of aggregating information and forming a comprehensive understanding of the literature.

Figure 2

Combining Basic Flow Diagram for Studies



Note: From "Basics of random effect meta-analysis with basic steps in R", by Paracha et al., 2017, Kindle. See Appendix A for permission to use.

Advantages

One advantage of using a random effect meta-analysis was its ability to simplify complex data. Combining and analyzing data from multiple studies, a random effect meta-analysis can provide a more comprehensive understanding of a particular research topic. Additionally, a random effect meta-analysis increases the sample size, enhancing the findings' statistical power. This method also utilizes existing data, reducing the need for new data collection and saving time, cost, and intrusiveness in the research process (Ellis, 2020).

Stone and Rosopa (2017) further outlined the advantages of random effect meta-analysis. First, the random effect meta-analysis results often improve estimates compared to individual studies, providing a more extensive data set to draw conclusions. Second, random effect meta-analysis increases the findings' accuracy and enhances the analysis's statistical power. Third, meta-analytic summaries can be applied to hypothesis testing, allowing researchers to test their hypotheses on a larger scale. Additionally, random effect meta-analysis can help identify publication bias, ensuring that all relevant studies were included in the analysis. Finally, random effect meta-analysis can identify moderators that may influence the relationship between variables, providing valuable insights into the research topic.

According to Patten and Newhart (2017), random effect meta-analysis was a valuable tool, as it synthesizes results from independent researchers, offering a comprehensive overview of the existing literature on a specific topic. By combining and analyzing data from multiple studies, random effect meta-analysis provides a more robust and reliable understanding of the research question. Radom effect meta-analysis increases the sample population.

Disadvantages

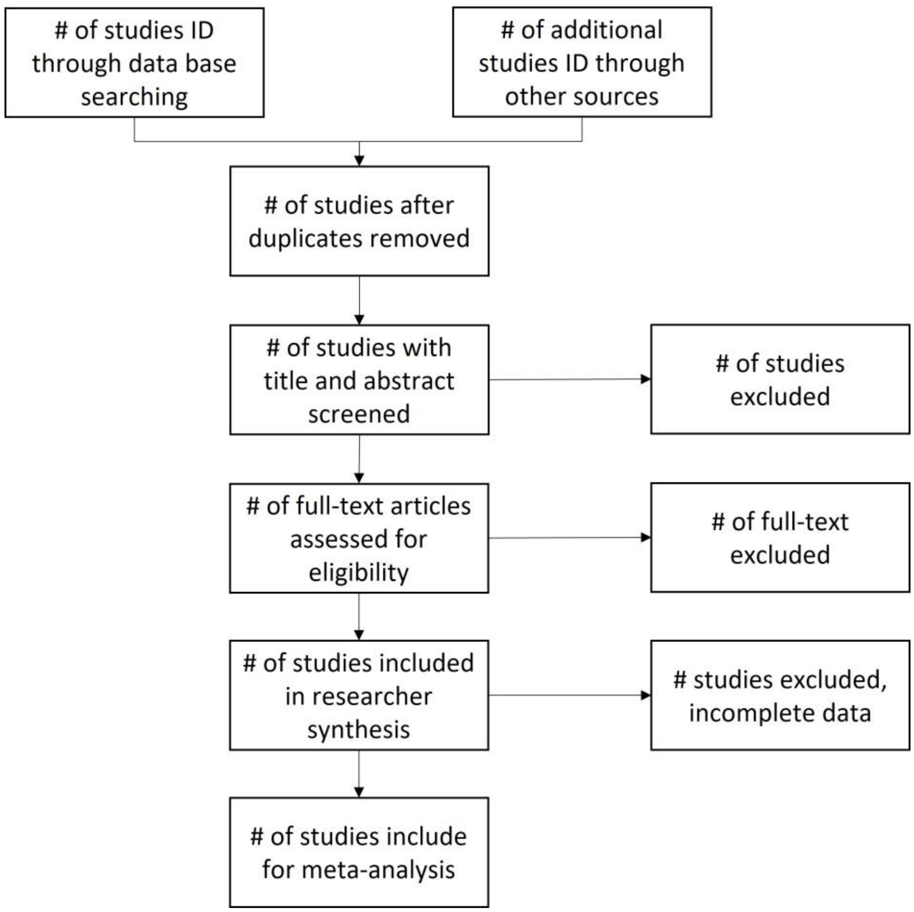
According to Schmidt (2017), conducting random effect meta-analysis regression in research has several potential pitfalls. These include the possibility of inflated correlation coefficients due to small sample sizes, the risk of variable selection bias by focusing only on high correlations, low statistical power resulting from small sample sizes, the likelihood of outlier data points having a more significant impact due to small sample sizes, the reliance on unstandardized regression weights and the use of only the smallest p-values. Additionally, biases in the dependent variable may not be corrected, measurement error in predictor variables may not be accounted for, the dependent variable may be unreliable due to sampling error, and omissions of moderators in cases of missing data. Allen (2020) highlights a challenge in a random effect meta-analysis of converting various metrics used in individual studies into a common metric that can be used across the selected studies. This process can be demanding and requires careful consideration to ensure an accurate comparison and synthesis of findings.

Study Selection Criteria

In order to determine which studies to include in a random effect meta-analysis, I will establish a selection criterion. As noted by Harari et al. (2020), the choice of database and keywords can influence the quality of the outcomes. Therefore, I conducted a Boolean Logic database search using the keywords "COVID-19," "intelligent analytics," and "supply chain resiliency," as suggested by Hansen et al. (2021). To ensure the inclusion of relevant studies, I used four data attributes as my selection criteria. First, studies must include at least one predictor and the dependent variable of interest: COVID, IA, and the SCR. Second, studies that examine the relationship between one predictor variable and a dependent variable will also be considered. Third, only studies that were independent and not duplicates will be included. Finally, the studies must provide statistical data such as ES, standard deviation, means, sample size, and statistical methods. These criteria will help ensure that high-quality studies were included in the random effect meta-analysis. A visual representation of the study selection criteria can be found in Figure 3. By adhering to these criteria, I am confident that the resulting random effect meta-analysis provided a thorough and reliable synthesis of the available literature.

Figure 3

Basic flow diagram for selection criteria



Note: Adapted from "Basics of random effect meta-analysis with basic steps in R", by Paracha et al., 2017, Kindle. See Appendix A for permission to use.

Data Analysis

The data examined for this study was from the perspective of the research question. To what extent, if any, is there a relationship of COVID on SCR and IA on SCR? The hypothesis testing answers the research question.

Null Hypothesis (H_0): There is no statistically significant relationship of COVID on SCR nor IA on SCR.

Alternative Hypothesis (H_1): There is a statistically significant relationship of COVID on SCR and IA on SCR.

Statistical Test

Statistical testing allows the researcher to analyze observed phenomena mathematically. The researcher uses regression analysis to investigate relationships between variables (Wang, 2018). The researcher uses the advantages of nonlinear regression, such as simplicity, flexibility, and parsimony, to form a statistical analysis of a phenomenon (Glaz & Yeater, 2020).

I use meta-regression analysis for this study to form statistical correlations that answer the hypothesis. Meta-regression can estimate arbitrary relationships between variables (Fernández-Corté, 2021). The predictor variables COVID-19 and IA were not linear functions. The researcher uses non-linear regression analysis to accurately analyze the interactions between predictor and dependent variables (Kenton, 2021). This study correlates COVID, IA, and SCR. The best statistical analysis was a random effect meta-regression.

Statistical testing was a valuable tool for researchers to analyze observed phenomena mathematically. Regression analysis, specifically nonlinear regression, allows researchers to investigate relationships between variables (Glaz & Yeater, 2020; Wang, 2018). I will employ random effect meta-regression analysis in this study to establish statistical correlations that address the research hypothesis. Meta-regression offers the advantage of estimating arbitrary relationships between variables (IBM, n.d.). This study examines the correlations of COVID on SCR and IA on SCR. A random effect meta-regression was the most appropriate statistical analysis approach.

Cohen's *d* is widely recognized as an appropriate ES for comparing means between two groups. ESs play a crucial role in research, particularly random effect meta-analysis studies (McLeod, 2023). Researchers were constantly reminded of the importance of reporting ESs because of their immense usefulness in three keyways. First, ESs provide a standardized metric for presenting the magnitude of reported effects. This standardization allows for easy comprehension, regardless of the measuring scheme for the dependent variable. Researchers can effectively communicate the practical significance of their findings by utilizing standardized ESs such as Cohen's *d*, going beyond merely reporting statistical significance. Cohen’s *d* was crucial in conveying the real-world impact of the results to academic and non-academic audiences. Second, ESs facilitate the drawing of meta-analytic conclusions by allowing comparisons of standardized ESs across multiple studies. By examining ESs in different contexts and populations, researchers can better understand the overall impact and generalizability of observed effects. This meta-analytic approach enhances the robustness and reliability of scientific findings, advancing knowledge in the field. Lastly, ESs from previous studies can be used when planning new research. By incorporating the ESs reported in the prior literature, researchers can estimate the potential ESs to expect in their study. ES assists in sample size calculations and study design and improves future research endeavors' overall efficiency and validity.

Data Cleaning

The researcher can access relevant, reliable data on the investigated phenomena (Corrales et al., 2018). To ensure data integrity, a thorough data cleaning process was employed (Kohler & Link, 2021), reducing the risk of corrupt data. The data sets used in this study were sourced from peer-reviewed publications, ensuring a minimum standard of data integrity. Additionally, a visual investigation was conducted to verify the accuracy of data copying from the original articles. The study data set was securely stored on a Toshiba one-terabyte external drive, kept in a locked cabinet accessible only by the researcher.

Missing Data

As an independent researcher, I understand the importance of data quality and the need to identify missing data in data sets. In order to ensure accurate and reliable data, it was crucial to assess various aspects such as accuracy, coherence, uniqueness, compliance, and completeness (Ezzine & Benhlima, 2018). Several strategies can be employed to manage missing data effectively. First, it was essential to thoroughly inspect the data sets for missing values to ensure completeness. Additionally, clearly understanding the specific information sought from the data set can help identify potential gaps. Triangulation, a method involving multiple sources or techniques to confirm findings, can also be used to check for missing data. Researchers can identify discrepancies and potential missing values by cross-referencing data sources or conducting parallel analysis. Lastly, performing a sensitivity analysis of the data can provide awareness of the possible impact of missing data on the overall analysis. This analysis allows researchers to assess the robustness and reliability of their results, even in the presence of missing values (Papageorgiou et al., 2018).

Identifying and Testing Assumptions

In meta-regression, four key assumptions need consideration: (a) normal distribution of residuals, (b) homogeneity of variances (Parchami et al., 2017), (c) independence of variables (Fortin, 2014), and (d) identification of outliers. To check for normal distribution, I examined the data histogram. A two-way contingency table analysis test assessed the homogeneity of variances by inspecting the scatter plot for equal variances, determining the presence of any relationship between the predictor variables. A method to test outliers was through boxplots and univariate tests. In the event of any violation of these assumptions, several steps should be taken: (a) verify the correctness of the research question and hypotheses, (b) ensure accurate data copying during the evaluation process, (c) verify the correctness of the data scales, (d) review the statistical evaluation method used, and (e) correct any identified errors before rerunning the analysis.

Inferential Results

The researcher uses a random effect meta-analysis to take existing data and form new paradigms on the phenomenon (Ellis, 2020). Radom effect meta-analysis has four analytical steps: (a) determining ES, (b) using weighted mean ES, (c) determining the confidence interval of ES, and (d) interpreting results (Borenstein et al., 2021; Ellis, 2020; Paracha et al., 2017). Using the random effect meta-analysis data, the researcher develops a database for inferential statistics.

Inferential statistics process (a) the population under study, (b) determine a sample that represents the population, (c) determine the statistical analysis method, and (d) draw conclusions from the analysis (Saunders et al., 2019). The use of regression analysis predicts correlations between predictor and dependent variables. To test for correlation in statistical analysis, the statistical significance value $< .05$ infers that the variables show correlation with a 5% probability that the outcome was by chance (Dawson, 2008). The researcher uses significant values to test the null hypothesis (Borenstein et al., 2021). Correlation does not infer causality. In a study, ES determines the strength of the correlation (Borenstein et al., 2021; Paracha et al., 2017).

In research, random effect meta-analysis was a valuable tool for synthesizing existing data and generating new insights and paradigms on a particular phenomenon (Ellis, 2020). The process of conducting a random effect meta-analysis involves four key analytical steps. First, the researcher determines the ES, quantifying the magnitude of the relationship between variables. Second, considering the sample sizes of the articles included in the study, a weighted mean ES was determined. Third, the confidence interval of the ES was determined, providing a range within which the true ES was likely to fall. Finally, the random effect meta-analysis results were interpreted, highlighting the general patterns and trends observed (Borenstein et al., 2021; Ellis, 2020; Paracha et al., 2017).

Completing the random effect meta-analysis, the researcher can develop a database for inferential statistics. Inferential statistics involve several steps. First, identify the population under study, representing the broader group to which the conclusions will be generalized. Secondly, a sample was carefully selected to ensure it was representative of the population. Third, the appropriate statistical analysis method, such as regression analysis, predicts correlations between predictor and dependent variables.

The statistical significance value was used to test for correlation in statistical analysis. A significance value of < 0.05 indicates that chance was not likely for the observed correlation between variables, with a probability of 5% or less. It was important to note that the correlation does not infer causality but indicates a relationship between the variables under investigation (Dawson, 2008). The ES in a study indicates the strength of the correlation, allowing researchers to assess the practical significance of the findings (Borenstein et al., 2021; Paracha et al., 2017).

Software

Processing large data sets can become overwhelming without a computer software package (Janev & Mojanoski, 2017). Researchers use statistical software packages to understand the statistical analysis of the phenomenon (Rode & Ringel, 2019). The statistical software package used in this study was the IBM Statistical Package for the Social Sciences (SPSS) for Windows version 28 and Minitab.

The efficient processing of large data sets can be a daunting task without the assistance of a reliable computer software package (Janev & Mojanoski, 2017). To gain a comprehensive understanding of the statistical analysis of a given phenomenon, researchers often rely on specialized statistical software packages (Rode & Ringel, 2019). In this study, I used the IBM Statistical Package for the Social Sciences (SPSS) for Windows version 28 and Minitab as statistical software packages.

Study Validity

Reliability and validity are essential attributes that measurement scales must possess in quantitative research. Reliability refers to the extent to which a measuring instrument controls errors and produces consistent results across multiple trials or studies (Mohajan, 2017). It ensures that the same results were obtained when the research was repeated. On the other hand, validity refers to the appropriateness, accuracy, and generalizability of measurement scales in capturing the intended phenomena (Saunders et al., 2019). According to Saunders et al. (2019), reliability is associated with replication, meaning research findings should be consistent and reproducible. Consistent and reproducible allow the reliability of the study to be evaluated and verified. Validity ensures that the data collected and used for the analysis were valid and free of ambiguity. Validity ensures that the measurement scales accurately measure the correct requirements. Reliability and validity are crucial in quantitative business research, providing a framework to ensure that research follows rigorous processes and design methods (Cypress, 2017). They ensure that the data collected were reliable and valid, increasing the credibility and precision of the research findings. Without reliability, research may produce inconsistent and unreliable results, while without validity, there may be doubts about the accuracy and relevance of the data collected.

Internal Validity

Cooper (2020) raised concerns regarding the validity of secondary data sets. It was crucial to verify the precision and appropriateness of the measures used in the original data collection (Saunders et al., 2019). The methodology used in collecting secondary data ensures the reliability and validity of the information. Publication bias, in which researchers selectively choose studies with stronger ES, can lead to Type II errors (Paracha et al., 2017). To assess publication bias, researchers can create a funnel plot. Table 2 visually presents the issues and solutions to improve the validity of a random effect meta-analysis.

Table 2

Threats to Radom effect meta-analysis and Protecting Validity

Validity Issues	Protecting Validity
Publication Bias	Conduct broad literature search for study inclusion
	Provide (if available) indices for retrieval bias
Incorrectly retravel of study information	Coder training
Unreliability of coding	
Change criteria of codes from one study to another	Peer review coding
Only some effect size are coded	
Causal relationships are differed when not supported	Ensure conceptual and metrological judgement is used
Influence of expectations	Justify weighting scheme
	Use as many of design characteristics as possible
Significant levels not adjusted	Be explicit of assumptions used
Lack of statistical independence for effect size	Describe approach to statistical considerations and nature of the problem being study
Weight of studies are not against the proportion of precision	
Homogeneity suffer for low statistical power	Validity of interpretation rules
Unjustified use of fixed effect models	
Missing effect size in preliminary studies	Explicitly what conversions used when incomplete or erroneous data is encountered
Restrict range of primary studies	
Wrong effect size with moderator	Analyze data using multiple procedures
Over generalization	
Failure of test heterogeneity in effect size	Summarize sample characteristics of individual in separate studies
Not enough statistical powered to uncover findings	
Cannot test effect holds across variations	
Omission of synthesis procedures	Employ meta-analysis reporting standards (MARS)

Note: Data derived from "*Research synthesis and random effect meta-analysis*" by Cooper (2020).

According to Derrick and White (2017), the independent sample t-test was robust against Type I errors at a significance level of 5%. A type I error occurs when two variables are considered related, leading to the rejection of the null hypothesis when it should not. Patten and Newhart (2017) suggested that the independent samples t-test was suitable for overcoming Type I errors. It allows for comparing two predictor variables (Abbott, 2017). Poncet et al. (2016) argued that the independent samples t-test has greater power than other t-tests associated with normal and uniform distributions.

External Validity

External validity, encompassing generalizability and applicability (Murad et al., 2018), was a crucial aspect of the investigation. In the case of this random effect meta-analysis, the selection criteria employed allow for the generalization of the study findings to the target population by carefully selecting relevant variables (Cooper, 2020). By incorporating multiple studies, the random effect meta-analysis provides a robust framework to ensure external validity (Avellar et al., 2017). A random effect meta-analysis improves the research study's external validity (Akhter et al., 2019). Furthermore, the correct coding of included studies by researchers contributes to establishing external validity (Pigott & Polanin, 2020). In this study, selection criteria were applied in business domains, effectively reducing potential threats to external validity.

Transition and Summary

Section 2 of this study began with a restated purpose statement. Section 2 contains discussions on (a) the role of the researchers as the primary data collection instrument, (b) there were no human participants, (c) the use of the quantitative method and correlation design, (d) the use of a random effect meta-analysis literature search for sampling, (e) ethical research considerations, (f) the data collection instrument, (g) a random effect meta-analysis as a data collection technique, (h) how the data analysis performed, (i) the validity of the study.

Section 3 contains the study research. The introduction to Section 3 begins with a restatement of the purpose of the study as a first sentence and a summary of the findings. Section 3 covers topics of (a) presentation of the findings, (b) applicability of the findings with respect to professional practices of business, (c) implications for social change, (d) recommendations of action, (e) recommendations for further research, (f) reflections on the researcher’s experience, (g) conclusion and (h) appendices.

Section 2 of the study begins by restating the purpose statement. It then delves into several vital discussions, namely: (a) The role of researchers as the primary data collection instrument; (b) The absence of human participants in the study; (c) The use of the quantitative method and correlation design; (d) The use of a random effect meta-analysis literature search for sampling; (e) Ethical considerations in research; (f) The data collection instrument employed; (g) The use of random effect meta-analysis as a data collection technique; (h) Details on how the data analysis was conducted; (i) The validity of the study.

Moving on to Section 3, it consists of the actual research findings. The introduction to this section begins with a restatement of the purpose of the study, followed by a summary of the findings. The topics covered in Section 3 were as follows: (a) Presentation of the findings; (b) Applicability of the findings to professional business practices; (c) Consequences for social change; (d) Recommendations for action; (e)

Suggestions for further research; (f) Reflections on the researcher's experience; (g) Conclusion; (h) Appendices. The study provided the researcher with a comprehensive understanding of the research and its implications for contributing to the existing body of knowledge by addressing these topics.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlation study was to examine the relationships between COVID on SCR and IA on SCR. For this purpose, in this study, I addressed the following research question: Is there a statistically significant relationship of (a) COVID on SCR and (b) IA on SCR? To examine these relationships, I applied the meta-analysis approach by testing whether the effect sizes of these relationships reported in published studies are consistent across these studies. The sample comprised a total of 41 studies published between 2019 and 2023 that tested these relationships. This study used Egger's regression and the homogeneity test of ES for the meta-analysis. In the following, I present the analysis results and findings in detail.

Presentation of the Findings

This section presents the key analysis components of the random-effects meta-analysis. Random-effects meta-analysis/regression allows researchers to combine and analyze data from multiple studies, providing a comprehensive overview of the relationship between variables (Borenstein et al., 2021). The use of Cohen's *d* for effect sizes quantifies the magnitude of the relationship (Cohen, 1992). The equations presented in this study were used to calculate the effect sizes based on the parameters provided. Testing for homogeneity and addressing publication bias are crucial steps in ensuring the validity and generalizability of meta-analysis results.

Random-effects meta-analysis gathers information from articles on selection criteria, often with different characteristics (Ellis, 2020). These characteristics often drive the homogeneity of random-effects meta-analysis. Homogeneity testing is an essential step in meta-analysis. Homogeneity refers to the similarity of effect sizes in all studies. If the effect sizes are consistent, the true effect size will likely be the same across different populations and settings (Sebhatu et al., 2020). However, heterogeneity indicates that effect sizes vary substantially, which may be due to differences in study designs, sample characteristics, or other factors. Heterogeneity can be assessed using statistical tests such as the Q-test or the I-squared statistic.

If the research reveals heterogeneity, a sufficient explanation of the effects of the characteristics on the analysis requires an explanation to ensure that the data and models support validity. During the analysis of the data of the selected studies, heterogeneity was significant enough to warrant further investigation of the effect of COVID on SCR. The following sections provide a descriptive statistical analysis of the inferential section and a summary of the findings of this study.

As a researcher, I must consider publication bias in the meta-analysis. This refers to the selective publication of studies based on the direction or significance of their findings. If only researchers publish studies with significant results, they may distort the overall effect estimate. Therefore, assessing and addressing publication bias is essential by conducting funnel plot analysis or statistical tests, such as Egger's regression test. The following sections will provide empirical evidence of the data to answer the research question and the hypotheses.

Hypotheses

Hypotheses use a negative and a positive as a dichotomy to provide statistical evaluation of data that may or may not form correlations (Levine, 2022). Establishing hypotheses forms a binary decision for the researcher to accept the infernal results or reject the results as a truth (Li & Tong, 2020). The hypothesis of this study was as follows:

H_0: There is no statistically significant relationship of (a) COVID on SCR nor (b) IA on SCR.

H_1: There is a statistically significant relationship exists between (a) COVID on SCR and (b)IA on SCR.

Testing these hypotheses changes the analysis into two sub-analyses: (a) COVID on SCR and (b) IA on SCR. To test these hypotheses using meta-analysis, I divided them into the following two sets of hypotheses:

$H1_0$: The ES of COVID on SCR is not consistent across the studies.

$H1_1$: The ES of COVID on SCR is consistent across the studies.

$H2_0$: The ES of IA on SCR is not consistent across the studies.

$H2_1$: The ES of IA on SCR is consistent across the studies.

The analytics of these hypotheses of accepting or rejecting $H1_0$ and $H2_0$ will be discussed later in this study.

Random-effects meta-analysis and meta-regression allow researchers to establish statistical relevance to studies in the same general topic area (Khan & Khan, 2021). Additionally, researchers can form generalities across a broad spectrum. However, since a random-effects meta-analysis is a statistical review of studies, an investigation was performed to test for homogeneity. Although a random effect meta-analysis can lead to the interpretation of ES and significance (*p*) used to determine the relationship between the predictor and dependent variables, the analysis revealed that an investigation of heterogeneity was warranted for the selected studies of COVID on SCR to investigate heterogeneity. Heterogeneity can affect the validity of a random-effects meta-analysis if it is not explainable.

Meta-Analysis Test Methods

Meta-analysis is done in three steps. The first step is to test the homogeneity of observed ES. If researchers were to conduct multiple identical studies using the same methods and population, the observed variation in ES across these studies would approximate the variation estimated under the central limit theorem (Jackson et al., 2020). However, in the literature, studies were conducted in different locations and at different times. Different data collection methods, measurement instruments, and research designs were used (Schmid et al., 2020). These variations in methods and populations can increase observed variation well beyond the anticipated variation estimated under the central limit theorem.

The test of homogeneity of ES assesses whether the observed variation in ES is significantly larger than the estimated variation. Homogeneity of effect sizes refers to the consistency of effect sizes across different groups. In the context of meta-analysis, it is essential to assess whether associations between factors are consistent across various subgroups (Braun & Clarke, 2021). This assessment helps researchers understand whether the observed effects are stable and generalizable. Testing for homogeneity is done by looking at the Q statistic, degrees of freedom, and Q significance. The system is homogenous if the Q statistic is less than the degrees of freedom and the Q significance is greater than .05. If this test is not significant, the researcher may reject the null hypothesis that ES is not consistent across the studies.

Second, if the difference between observed and estimated variation in ES is significant, the researcher needs to investigate study-level characteristics. Egger's meta-regression is widely used to test the effects of study-level characteristics on ES variation across studies. Egger's regression test is a common test used to assess potential publication bias in a meta-analysis. It involves analyzing funnel plot asymmetry by performing a linear regression of the intervention effect estimates against their standard errors, weighted by their inverse variance (Rodgers & Pustejovsky, 2021). The test checks for potential bias in the distribution of study results, especially when the sample size is small or when other factors affect the relationship between effect size and standard error (Furuya-Kanamori et al., 2020). Egger's regression test determines the symmetry of the funnel plot, which is a pictorial representation of publication bias. If the intercept is close to zero, then the indication is that there is no publication bias.

Third, once the researcher identifies study-level characteristics that significantly influence the variation in ES, they test the homogeneity of ES using residuals from Egger's meta-regression. In other words, they examine whether after accounting for these study-level characteristics, the residual ES is consistent across these studies.

Variables and Descriptive Statistics

ES serves as a quantitative measure of the strength and direction of a relationship and may constitute more importance than α for significance (Peterson, 2021). It was important to note that a larger value indicates a stronger relationship. Cohen's *d* was a widely used method for determining ES in research studies. Using ES, researchers can compare the strength of the relationship between different studies and populations, facilitating the comparison of results and formulation of general conclusions. This study used d_{calc} as the effect size measure. Cohen's d is a widely used metric in the social and behavioral sciences to determine the magnitude of the effect (Ellis, 2020). ES was used to estimate a common underlying effect, and sometimes, the effect and its heterogeneity were modeled as a function of the characteristics of the studies (Song et al., 2020).

Descriptive statistics are an essential aspect of statistical analysis that summarizes the data. This helps simplify cumbersome data sets and extract meaningful information. As Groeben and Pieper (2019) stated, descriptive statistics employ measures such as frequency distributions, central tendency, and measures of variability to provide a comprehensive view of the dataset. Researchers can identify data patterns, trends, and outliers using graphical and numerical methods.

Measures of variability and standard deviation serve as crucial components of descriptive statistics. The standard deviation measures the deviation of each data point from the mean. Hallgren (2019) states that a higher standard deviation indicates more significant variability, whereas a lower standard deviation indicates a more uniform pattern in the data.

Initially, I identified 371 articles for inclusion. Initially, 63 articles were excluded through rigorous selection, resulting in a pool of 308 articles for evaluation. Further scrutiny led to an additional 161 articles being excluded due to the absence of numerical data necessary for the regression analysis, leaving a final sample of 147 articles. Of these 147 articles, 106 were eliminated due to incorrect or insufficient data to perform calculations, resulting in a final analysis dataset of 41 articles. Specifically, 20 studies focused on COVID on SCR, while 21 explored IA on SCR. The data of these 41 articles consisted of a parametric variable β.

The data collected were analyzed using SPSS version 28 software. The 40 articles described 54 analysis groups, with (a) 24 groups investigating COVID on SCR and (b) 30 groups investigating IA on SCR. The total number of participants in all articles included in this study was 13,443, with a minimum of 102 participants and a maximum of 3,132 participants. Appendix B provides a detailed description of the variables used in the analysis and of the authors of the articles. Appendix C contains the database used for the analysis, and Appendix D presents an exemplar abstract. Appendix C contains the database used for the analysis, and Appendix D presents an exemplar abstract.

The equations presented in this study were used to calculate the effect sizes based on the parameters provided. Equation 1 (EQ1) calculates the standard error of the β estimate (SEβ) using the sample size (n) and the estimated coefficient (β) from the selected studies. Equation 2 (EQ2) calculates Cohen's d using the estimated coefficient (β) and standard error (SE_β). Equation 3 (EQ3) calculates the standard error of the estimate of the effect size (SEd) based on the standard error (SE_β) and the estimated coefficient (β). Using β as the starting variable, finally solved for d_{calc} and SE_{dcalc}. According to Becker (2020), given β, the equation for calculating Cohen's d is as follows:

EQ1: $SE_{\beta} = \sqrt{\frac{1-\beta^2}{n}}$

EQ2: $d = \sqrt{\frac{\beta^2}{1-\beta^2}}$

EQ3: $SE_{d} = \frac{SE_{\beta}}{\sqrt{1-\beta^2}}$

Where:

SE_{β} = the standard error term associated with β

β = slope coefficient provided from the selected studies

n = the sample size

t = is the measured difference of the sample mean ($\bar{x}$) from the population mean (μ)

d = Cohen's *d* (effect size)

Table 3

Cohen's Effect Size Description

COHEN'S *d*	Interpretation
d = 0.2	Small effect
d = 0.5	Medium effect
d = 0.8	Large effect

COVID Descriptive Statistics

Descriptive statistical analysis played a crucial role in understanding the data collected from the articles included in the study. Table 4 shows the descriptive statistics of COVID on SCR. Cohen's d is a standardized measure of effect size that indicates the strength and direction of effects by the predictor variable on the dependent variable. In this case, it is used to quantify the magnitude of the effect of COVID on SCR. The mean effect size (d) was calculated for the COVID on SCR group, with a value of 0.36 and an SD of .09. Furthermore, Table 4 suggests that the two subgroups influenced *d*, publication year (Pub Yr), and the statistical method (Meth). The mean values of *Pub Yr* and *Meth* were respectively 1.67 and 0.46 SD of 1.01 and 0.51. This implies that *Pub Yr* has a large uncertainty associated with the distribution, while *Meth* has a moderate uncertainty.

Table 4

COVID on SCR Descriptive Statistics

	N	Min	Max	Mean	SD
d (calc)	24	0.224	0.48	0.35554	0.085842
SEd (calc)	24	0.018	0.152	0.06704	0.027395
Pub Yr	24	0	3	1.67	1.007
Meth	24	0	1	0.46	0.509
Valid N (listwise)	24				

Figure 4 shows a forest plot of the effect sizes of all the selected studies included in this study. A forest plot visually represents the effect sizes and confidence intervals for each study in the analysis. It allows a quick comparison of effect sizes and helps identify outliers or influential studies. The overall effect size is represented by a diamond at the bottom, with the width of the diamond indicating the confidence interval. The effect size ranges from 0.22 to 0.48, suggesting a small to medium effect. Furthermore, the p-value was <.001, indicating a statistically significant effect. The confidence interval (CI) is lower at .32 and upper at 0.38, indicating that at the 95% confidence level, there is a less than .06% chance that the ES of new studies will fall outside the indicated CI.

The Shapiro-Wilk test of the normality of COVID ES was not significant ($W = 0.925$, $p = .075$), indicating that the distribution of COVID ES was not significantly different from the normal distribution. The histogram (Figure 5) is a pictorial representation of COVID normal distribution.

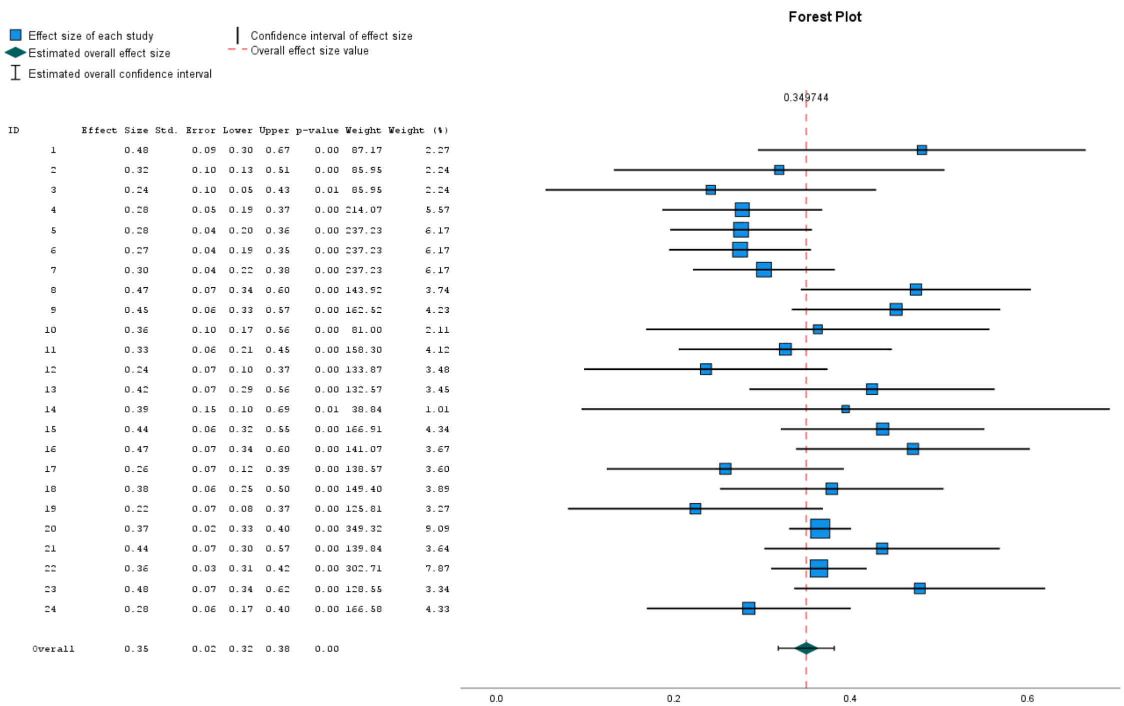
Table 5

Shapiro-Wilk Test

Parameter	DF	Statistics	p-value	Decision at level(5%)
d_{calc}	24	0.92477	0.07453	Can not reject normality

Figure 4

Forest Plot COVID on SCR

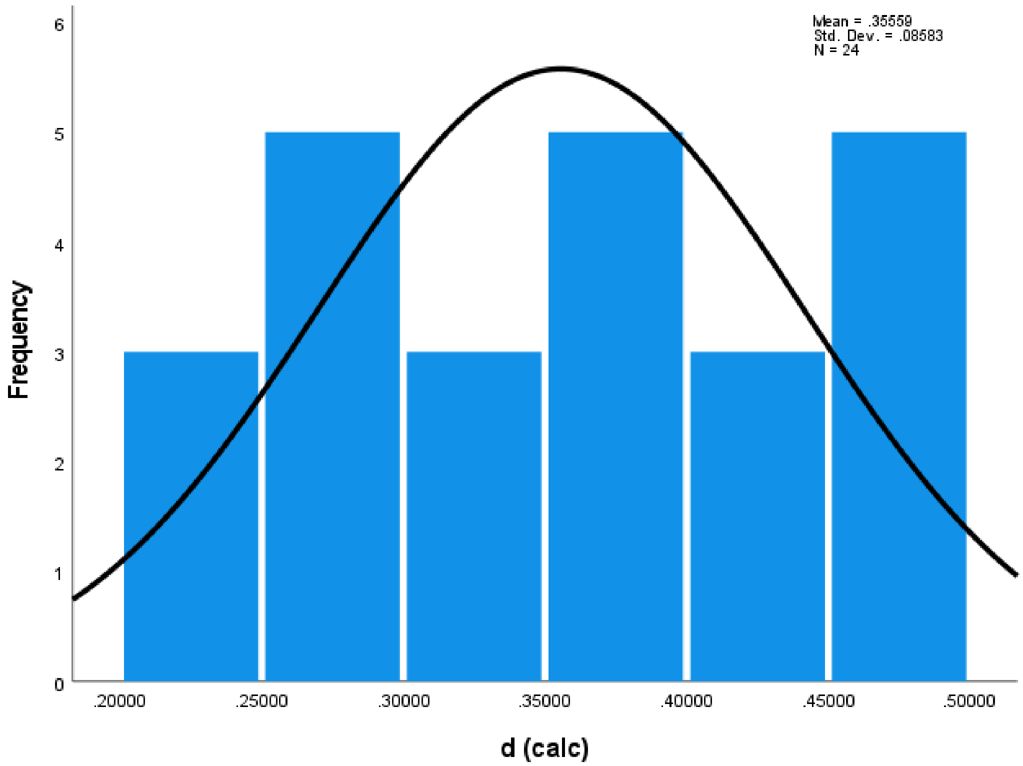


ID	Effect Size	Std. Error	Lower	Upper	p-value	Weight	Weight (%)
1	0.48	0.09	0.30	0.67	0.00	87.17	2.27
2	0.32	0.10	0.13	0.51	0.00	85.95	2.24
3	0.24	0.10	0.05	0.43	0.01	85.95	2.24
4	0.28	0.05	0.19	0.37	0.00	214.07	5.57
5	0.28	0.04	0.20	0.36	0.00	237.23	6.17
6	0.27	0.04	0.19	0.35	0.00	237.23	6.17
7	0.30	0.04	0.22	0.38	0.00	237.23	6.17
8	0.47	0.07	0.34	0.60	0.00	143.92	3.74
9	0.45	0.06	0.33	0.57	0.00	162.52	4.23
10	0.36	0.10	0.17	0.56	0.00	81.00	2.11
11	0.33	0.06	0.21	0.45	0.00	158.30	4.12
12	0.24	0.07	0.10	0.37	0.00	133.87	3.48
13	0.42	0.07	0.29	0.56	0.00	132.57	3.45
14	0.39	0.15	0.10	0.69	0.01	38.84	1.01
15	0.44	0.06	0.32	0.55	0.00	166.91	4.34
16	0.47	0.07	0.34	0.60	0.00	141.07	3.67
17	0.26	0.07	0.12	0.39	0.00	138.57	3.60
18	0.38	0.06	0.25	0.50	0.00	149.40	3.89
19	0.22	0.07	0.08	0.37	0.00	125.81	3.27
20	0.37	0.02	0.33	0.40	0.00	349.32	9.09
21	0.44	0.07	0.30	0.57	0.00	139.84	3.64
22	0.36	0.03	0.31	0.42	0.00	302.71	7.87
23	0.48	0.07	0.34	0.62	0.00	128.55	3.34
24	0.28	0.06	0.17	0.40	0.00	166.58	4.33
Overall	0.35	0.02	0.32	0.38	0.00		

Model: Random-effects model
Heterogeneity: Tau-squared = 0.00, H-squared = 1.98, I-squared = 0.50
Homogeneity: Q = 41.27, df = 23, p-value = 0.01
Test of overall effect size: z = 21.69, p-value = 0.00

Figure 5

COVID on SCR Cohen's d Distribution



IA Descriptive Statistics

A descriptive statistical analysis of the data collected on IA on SCR was performed. Data include summary statistics of mean, standard deviation, variance, skewness, and kurtosis. Table 6 shows the descriptive statistics of IA on SCR. Cohen's d is a standardized measure of effect size that indicates the strength and direction of effects by the predictor variable on the dependent variable. In this case, it is used to quantify the magnitude of the effect of IA on SCR. The mean effect size (*d*) was calculated for the IA on SCR group, with a value of 0.63 and an SD of .11. Furthermore, Table 6 suggests that the three subgroups influenced *d*, publication year (Pub Yr), geographical location (Loc), and the statistical method (Meth). The mean values of *Pub Yr*, *Loc*, and *Meth* were respectively 1.23, 0.67, and 1.17; SD of 1.01, 0.84. and 0.51. This implies that *Pub Yr* has a large uncertainty, *Loc* has a large uncertainty, and *Meth* has a low uncertainty.

Table 6

IA on SCR Descriptive Statistics

	N	Min	Max	Mean	SD
d(calc)	30	0.463	0.833	0.634867	0.107606
SEd(calc)	30	0.214	0.315	0.257233	0.024213
Pub Yr	30	0	3	1.23	1.006
Loc	30	0	2	0.67	0.844
Meth	30	0	2	1.17	0.648
Valid N (listwise)	30				

Figure 6 shows a forest plot of the effect sizes of all selected studies included in this study. A forest plot visually represents the effect sizes and confidence intervals for each study in the analysis. It allows a quick comparison of effect sizes and helps identify outliers or influential studies. The overall effect size is represented by a diamond at the bottom, with the width of the diamond indicating the confidence interval. The effect size ranges from 0.46 to 0.83, suggesting a medium to large effect. Furthermore, the p-value <.001, was indicating a statistically significant effect. The confidence interval (CI) is lower at .54 and upper at 0.73, indicating that at the 95% confidence level, there is a 95% chance that the ES of new studies will fall within the CI indicated.

The Shapiro-Wilk test of the normality of IA ES was not significant (W = 0.965, p = .420), indicating that the distribution of IA ES was not significantly different from the normal distribution. The histogram (Figure 7) is a pictorial representation of IA normal distribution.

Table 7

Shapiro-Wilk Test

Parameter	DF	Statistics	p-value	Decision at level(5%)
d_{calc}	30	0.96532	0.42021	Can not reject normality

Figure 6

Forest Plot IA on SCR

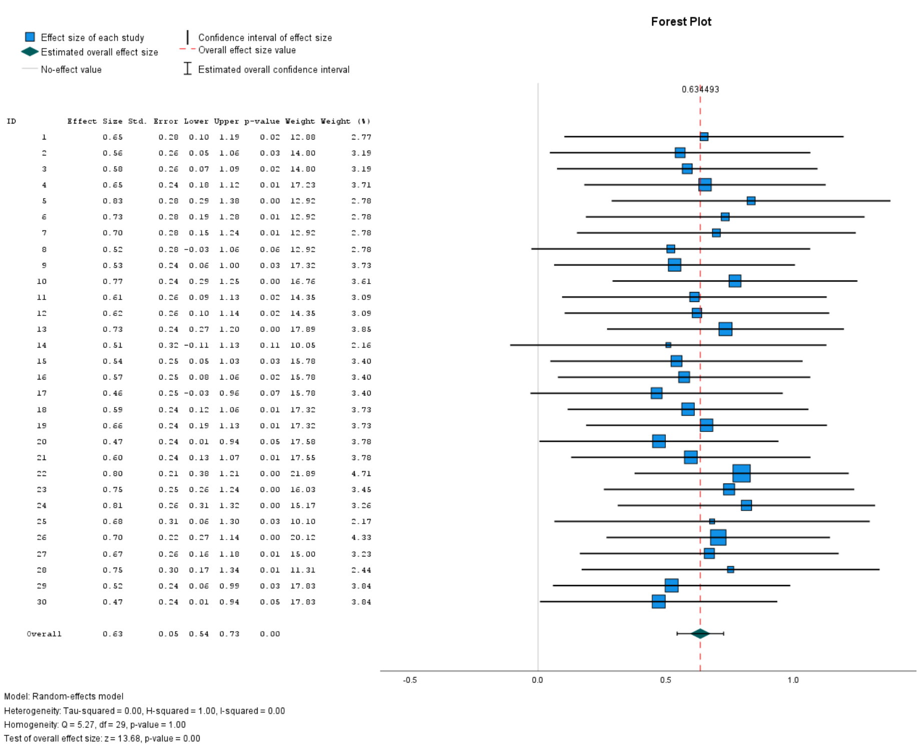
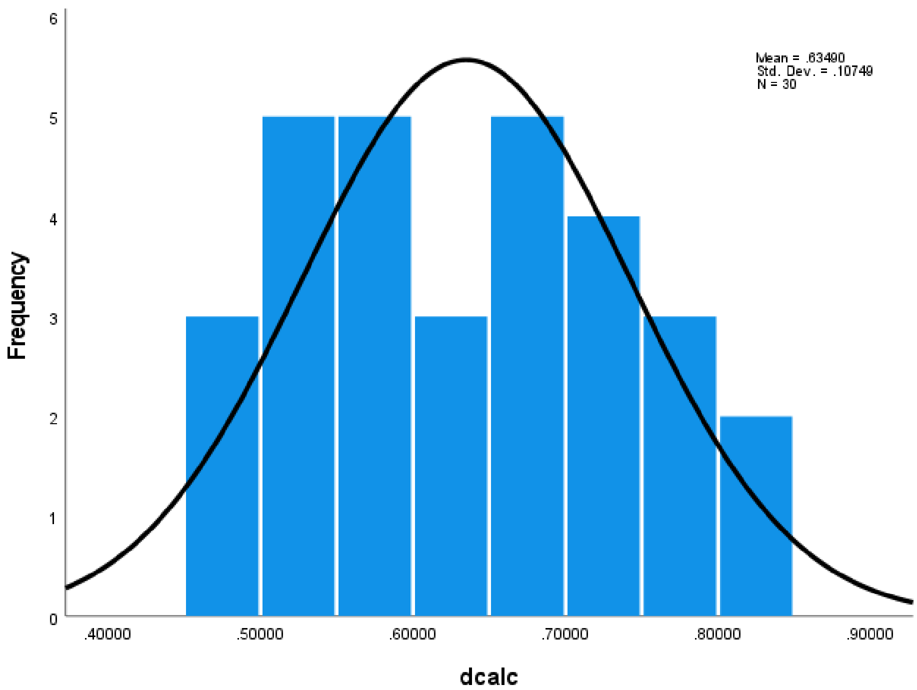


Figure 7

Histogram IA on SCR



Hypothesis 1 Testing (ES of COVID)

Using the following hypothesis:

$H1_0$: The ES of COVID on SCR is not consistent across the studies.

$H1_1$: The ES of COVID on SCR is consistent across the studies.

I used IBM SPSS ver 28 software to produce the analytics for ES of COVID on SCR through a meta-analysis/regression. The following is the analysis's determination to accept or reject $H1_0$.

In Table 8, the "Model 0" column shows the baseline homogeneity test results of COVID ES without controlling for any effects of study-level variables. In the top part of columns labeled "Model 1," "Model 2," and "Full Model" show the meta-regression results indicating the significance of study-level variables entered into the regression equation. The bottom part of these three columns shows the homogeneity test results of residual ES, i.e., the homogeneity after controlling for the study-level variables entered in the equation.

In Table 8, the homogeneity test results shown in the Model 0 column were not statistically significant, Q (23) = 41.272, p = .011, I^2 = 49.5, τ^2 = .003, H^2 = 1.981. These results indicate that the Null Hypothesis 1 cannot be rejected. To examine further the heterogeneity of ES, two study-level variables were entered into meta-regressions shown in the "Model 1," "Model 2," and "Full Model" columns. As shown in the Full Model column, the effects of pub year were significant, b = .038, t = 2.476, p = .022.

As shown in the Full Model columns in Table 8, when the effects of the two study-level variables are accounted for, the homogeneity of residual COVID ES was not significant, rejecting the null hypothesis that ES is not consistent across the studies. Compared to the baseline homogeneity test results, I^2 was reduced from 49% down to 25%, Q reduced down from 41.272 to 31.120. It indicates that the effects of study-level variables, particularly pub year, were the cause for failing to reject the Null Hypothesis 1. Conversely, these results reject the Null Hypothesis 1 when the effects of pub year is controlled,

The use of symmetry in a funnel plot infers the homogeneity of the results. Figure 8 was used as a pictorial representation to confirm the heterogeneity of the selected studies. The visualization in Figure 8, the interpretation of the funnel plot, shows that the data have some symmetry, indicating that there may not be as much heterogeneity as indicated in Table 9. However, due to the indication of heterogeneity, further investigation of the characteristics of the selected studies was warranted.

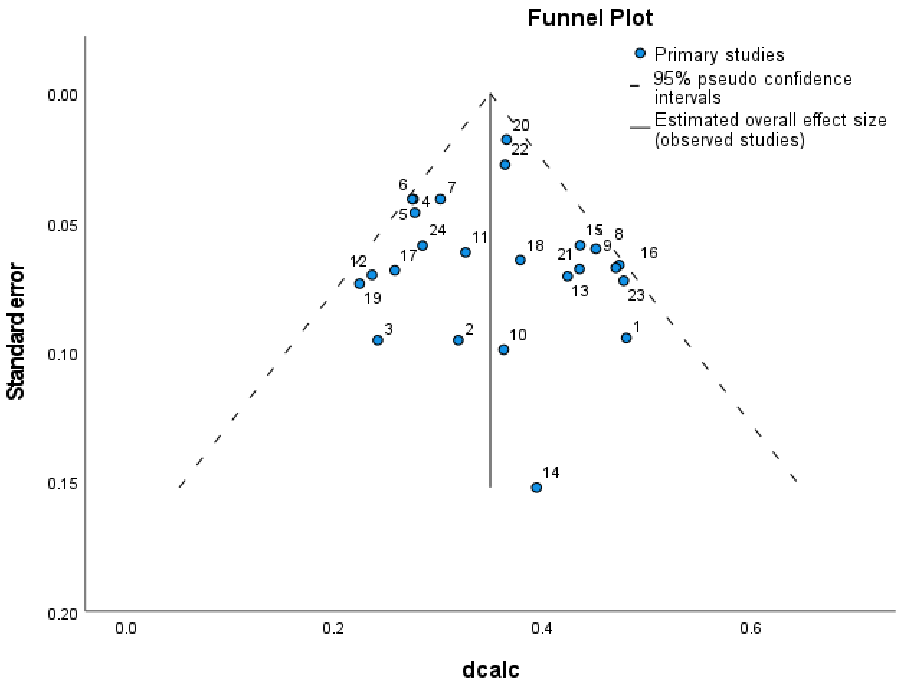
Table 8

Meta-Regression Analyses

Parmeter	Model 0	Model 1	Model 2	Full Model
Pub Yr	-	.041	-	.038
Meth	-	-	.011	-.001
Intercept	.350	.280	0.345	.286
Wald (X^2)	-	10.13	.106	6.464
Q-Statistic	41.272	31.135	40.177	31.120
Q-Sig. (X^2)	.011	0.093	0.010	.072
I^2	49.5	0	49.0	25.2
τ^2	.003	0	.003	.001
H^2	1.981	1	1.96	1.337

Figure 8

Funnel Plot COVID on SCR



Heterogeneity of COVID on SCR

With approximately half of the unaccounted heterogeneity in the outcome of interest across studies, an investigation of whether such heterogeneity may be further explained by differences in the characteristics of the studies, that is, year of publication (*Pub Yr*) and statistical methodology (*Method*). These characteristics were further investigated to determine whether possible inferences could be drawn from the selected studies to explain the heterogeneity.

I performed a meta-regression using IBM SPSS version 28 software to determine the effects of the characteristics. Meta-regression is a statistical method that can explore the sources of heterogeneity in a random-effects meta-analysis. A meta-regression software solution mathematically regresses ES on study-level covariates (moderators *Pub Yr* and *Method*), which may explain the outcome variation across studies. Meta-regression can also test the significance of covariate effects and estimate the adjusted pooled effect size after accounting for covariates.

Homogeneity is the assumption that all studies' true effect sizes are equal. To test this assumption, I performed a Q-test using the data provided. Table 8 indicates that the *Q* statistic was 41.272 (df = 23, p = .011), indicating heterogeneity in effect sizes between studies. The Q test indicated significant heterogeneity among effect sizes. Furthermore, the results in Table 8 indicate that the I^2 statistic was 49.5%, indicating moderate heterogeneity. The further collaboration in Table 8 is supported by $H^2 = 1.981$. Therefore, a conclusion forms that heterogeneity exists in the study's effect sizes.

Table 9 presents the analysis consisting of descriptive statistics of the three models: Model 1, Model 2, and the full model. In Model 1, the intercept had a value of 0.280 with a standard error (SE) of 0.0241. The t value of 11.601 indicated that the intercept significantly differed from zero, suggesting it significantly affected the outcome variable. The estimate of the parameters for *Pub Yr* was 0.041, with an SE of 0.0130. A t-value of 3.183 indicated that *Pub Yr* was also significantly different from zero, implying that it significantly impacted the outcome variable.

In Model 2, the intercept was 0.345, with an SE of 0.0215. The t value 16.081 indicated that the intercept significantly differed from zero, suggesting a significant effect on the outcome variable. However, the parameter estimate for *Meth* was 0.011, with an SE of 0.0336. A t-value of 0.325 indicated that *Meth* was not significantly different from zero, which implies that it did not have a significant impact on the outcome variable in Model 2.

In the full model, the intercept had a value of 0.286 with an SE of 0.0283. The *t value* of 10.118 indicated that the intercept significantly differed from zero, suggesting a significant effect on the outcome variable. The estimate of the parameters for *Pub Yr* was 0.038, with an SE of 0.0155. A *t*-value of 2.476 indicated that *Pub Yr* significantly differed from zero, implying that it significantly impacted the outcome variable. However, the parameter estimate for *Meth* was -0.001, with an SE of 0.0278. The *t value* of -0.033 indicated that *Meth* was not significantly different from zero, suggesting that its inclusion in the entire model did not have a significant effect on the outcome variable.

Table 9

Summary Meta-regression Analysis[a]

Parameter	Estimate	Std. Error[b]	t	Sig. (2-tailed)	95% Confidence Lower	95% Confidence Upper
Model 1:						
(Intercept)	0.280	0.0241	11.601	<.001	0.230	0.330
Pub Yr	0.041	0.0130	3.183	0.004	0.014	0.068
Model 2:						
(Intercept)	0.345	0.0215	16.081	<.001	0.301	0.39
Meth	0.011	0.0336	0.325	0.748	-0.059	0.081
Full Model:						
(Intercept)	0.286	0.0283	10.118	<.001	0.227	0.345
Pub Yr	0.038	0.0155	2.476	0.022	0.006	0.071
Meth	-0.001	0.0278	-0.033	0.974	-0.059	0.057

[a.] Random-effects meta-regression

[b.] Standard error of effect size

Table 10 provides information on the homogeneity and heterogeneity of the four parameters d_{calc}, d_{sub}, *Pub Yr*, and *Meth*. The Q-statistic measures the degree of heterogeneity within the data, and higher values indicate greater heterogeneity. The Q sig is the significance level of the Q statistic, indicating whether the heterogeneity is significant.

For d_{calc}, the *Q* statistic is 31.268, and the *Q sig* is 0.069, indicating some heterogeneity in the data but insignificant at the 0.05 level. The I^2 value is 26.3, suggesting that 26.3% of the variation in effect estimates is due to heterogeneity rather than chance. The H^2 value is 1.358, indicating that there may be some heterogeneity, but the effects are not overly large. The τ^2 value is 0.001, which represents the extent of variation in true effects between studies and is relatively low, suggesting that there is little variation of true effects between studies.

For the d_{sub}, the *Q* statistic is higher at 40.982, and the *Q sig* is lower at 0.008, indicating significant heterogeneity in the data. The I^2 value is also higher at 52.7%, indicating that more than half of the variation in effect estimates is due to heterogeneity. The H^2 value is 2.116, indicating that the effects are relatively large. The τ^2 value is also higher at 0.003, suggesting more variation in the true effects between studies.

Pub Yr has a Q statistic similar to Model 0, but the *Q sig* is higher at 0.091, suggesting that there may be some non-significant heterogeneity in the data. However, the value of I^2 is 0.0, suggesting that no heterogeneity is present in this model. The H^2 value is 1, indicating that the effects are insignificant, and the τ^2 value is 1.000, suggesting substantial variation in the true effects between studies.

Finally, for *Meth*, the *Q* statistic is 40.260, and the *Q sig* is 0.010, indicating significant heterogeneity in the data. The I^2 value is 49.1%, indicating that almost half of the variation in the effect estimates is due to heterogeneity. The H^2 value is 1.964, indicating that the effects are relatively large. The τ^2 value is 0.003, similar to the value for Model 1, suggesting some variation in the true effects between studies.

The analysis of Table 11 and Figure 9 provides insight into the dcalc and dsub effect sizes and sheds light on the underlying factors contributing to these differences. The observations made in Figure 9 point to a notable distinction in the dispersion between d_{sub} and d_{calc}. Specifically, d_{sub} exhibits a broader range of effect sizes, encompassing medium-to-large effects, while dcalc primarily reflects small-to-medium effects. This discrepancy strongly indicates that subgroups play a significant role in influencing the effect size of dcalc.

Furthermore, although there are certain similarities between the effect sizes and confidence intervals of d_{calc} and ds_{ub}, several other factors highlight the presence of dissimilarity. A notable difference lies in the dispersion of effect sizes, suggesting a potential variation in the homogeneity or heterogeneity of the subgroups. Additionally, independent variables that impact the effect size further differentiate sub from d_{calc}. These disparities provide valuable insights into the intricacies of the relationship between subgroups and effect sizes.

The detailed examination of Table 11 and Figure 9 delves into the nuances of effect size, uncovering crucial details about the variation, subgroup influence, and presence of independent variables. Given the significant findings in Model 0 and the full model, the inference suggests that the variables analyzed in these models significantly impact the outcomes measured in the random effects meta-analysis/regression. High chi-square values indicate variability among study results not due to chance alone. Models 0 and Full analyses provide valuable information on the effects of COVID on SCR and the effects of heterogeneity on ES analysis.

Table 12 provides insight into the original research question of the relationship between COVID and SCR. The analysis suggests that d_{calc} has the lowest level of heterogeneity, but this is not significant, while d_{sub} and *Meth* have significant heterogeneity. d_{sub} and *Meth* have high levels of heterogeneity. *Pub Yr* has no heterogeneity and a relatively large effect size. *Pub Yr* has no heterogeneity but a high variation in true effects between studies. These results suggest that the methodology used in the studies significantly influences dcalc, while the publication year does not significantly influence it.

Table10

Homogeneity and heterogeneity for d_{calc}, d_{sub}, Pub Yr, and Meth

Parameter	Q-statistic	sig.	I^2	H^2	τ^2
d_{calc}	31.268	0.069	26.3	1.358	0.001
d_{sub}	40.982	0.008	52.7	2.116	0.003
Pub Yr	31.281	0.091	0.0	1.000	0.000
Meth	40.260	0.010	49.1	1.964	0.003

Table 11

Combined Parametric for Forest Plot d and d_{sub}

Effect Size Estimates for Individual Studies (d_{calc})							Effect Size Estimates for Individual Studies (dsub)					
ID	ES	SE	95% CI		Wt	Wt (%)	ES	SE	95% CI		Wt	Wt (%)
			Lower	Upper					Lower	Upper		
1	0.738	1.5142	-2.23	3.705	0.402	0.7	0.365	1.5142	-2.602	3.333	0.417	0.5
2	1.382	1.5563	-1.668	4.433	0.382	0.6	1.948	1.5563	-1.103	4.998	0.395	0.4
3	1.445	1.5563	-1.606	4.495	0.382	0.6	2.62	1.5563	-0.43	5.67	0.395	0.4
4	0.977	0.87	-0.728	2.682	1.048	1.8	0.029	0.87	-1.676	1.735	1.156	1.3
5	0.271	0.9348	-1.561	2.103	0.934	1.6	0.532	0.9348	-1.3	2.365	1.019	1.1
6	0.271	0.9348	-1.561	2.103	0.934	1.6	0.645	0.9348	-1.188	2.477	1.019	1.1
7	0.271	0.9348	-1.561	2.103	0.934	1.6	0.688	0.9348	-1.14	2.521	1.019	1.1
8	0.096	0.128	-0.155	0.347	4.682	7.9	0.3	0.128	0.049	0.551	8.049	8.9
9	0.096	0.128	-0.155	0.347	4.682	7.9	0.3	0.128	0.049	0.551	8.049	8.9
10	1.233	1.7371	-2.171	4.638	0.311	0.5	1.261	1.7371	-2.144	4.666	0.32	0.4
11	1.712	0.1156	1.485	1.939	4.75	8	0.253	0.1156	0.027	0.48	8.25	9.1
12	1.262	0.316	0.643	1.881	3.366	5.7	0.925	0.316	0.305	1.544	4.814	5.3
13	0.972	0.3419	0.302	1.642	3.184	5.4	0.57	0.3419	-0.1	1.24	4.45	4.9
14	0.24	0.4898	-0.72	1.2	2.288	3.9	1.238	0.4898	0.278	2.198	2.875	3.2
15	0.377	0.2491	-0.112	0.865	3.858	6.5	0.7	0.2491	0.212	1.188	5.886	6.5
16	0.571	0.1797	0.219	0.923	4.358	7.4	1.173	0.1797	0.821	1.525	7.137	7.9
17	0.193	0.2259	-0.25	0.635	4.029	6.8	0.418	0.2259	-0.024	0.861	6.294	7
18	0.51	0.0316	0.448	0.572	5.046	8.5	0.952	0.0316	0.89	1.014	9.188	10.2
19	0.68	0.4804	-0.261	1.622	2.336	4	0.358	0.4804	-0.584	1.3	2.953	3.3
20	1.72	2.263	-2.715	6.156	0.188	0.3	0.787	2.263	-3.648	5.222	0.191	0.2
21	0.207	0.2026	-0.19	0.604	4.198	7.1	0.428	0.2026	0.031	0.825	6.717	7.4
22	2.422	1.785	-1.076	5.921	0.296	0.5	0.343	1.785	-3.156	3.841	0.304	0.3
23	0.245	0.4231	-0.585	1.074	2.658	4.5	0.569	0.4231	-0.26	1.399	3.486	3.9
24	0.243	0.2441	-0.236	0.721	3.895	6.6	1.472	0.2441	0.994	1.951	5.973	6.6
Overal	0.35	0.02	0.32	0.38			0.56	0.13	0.30	0.81		

Figure 9

Forest Plot Base and Full Model

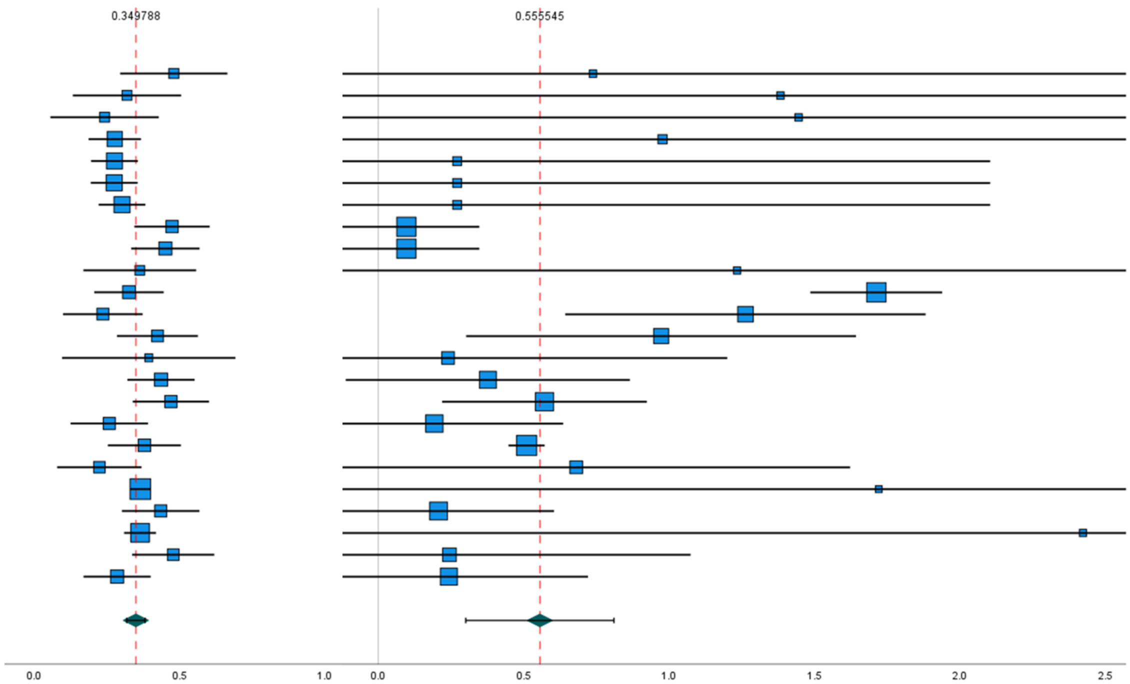


Table 12

Effect Size Estimates

					95% CI		95% PI[a]	
	Effect Size	Std. Error	Z	Sig. (2-tailed)	Lower	Upper	Lower	Upper
Overall	0.35	0.0161	21.66	0	0.318	0.381	0.24	0.46

[a] *Based on t-distribution.*

In summary, With a d_{calc} = 0.35 and p < .001 the H_0 was rejected, and H_1 accepted. with a Q statistic value of 41.272, df value of 23, p-value of .011, I^2 value of 26.3, and H^2 value of 1.964 indicates heterogeneity in effect sizes between studies. Thus, allows for accepting $H1_0$ that ES is not consistent across studies and rejecting $H1_1$.

Hypothesis 2 Testing (ES of IA)

Using the following hypothesis:

$H2_0$: The ES of IA on SCR is not consistent across the studies.

$H2_1$: The ES of IA on SCR is consistent across the studies.

I used IBM SPSS ver 28 software to produce the analytics for ES of COVID on SCR through a meta-analysis/regression. The following is an analysis to accept or reject $H1_0$.

In conducting a random-effects meta-analysis, it is essential to utilize various statistical measures to synthesize the findings of multiple studies into a single and comprehensive result. The parameters presented in Tables 13-15 are of significant importance in understanding the overall effect and the degree of variability or consistency observed in the included studies of IA on SCR. An inference was drawn by meticulously analyzing the results presented in these tables and drawing insightful conclusions.

The analysis findings in Tables 13-15 provide valuable information on the relationship between the intervention or IA in SCR and its impact on the results. Table 13 analysis revealed a *d* value of 0.634, which indicates a moderate effect according to commonly accepted benchmarks, as described in Table 3. This suggests that IA has a significant impact on SCR. Furthermore, the statistical significance of the effect, with a *p*-value < 0.001, indicates that the observed effect is unlikely to have occurred by chance alone.

The analysis of heterogeneity among the studies included in the random effect meta-analysis, as reflected in Table 14, did not demonstrate significant heterogeneity.

The Q statistic of 5.275, with 29 degrees of freedom and a significance level of 1, suggests that variations in study results can be attributed more to chance than to actual differences in effect sizes between studies. This conclusion, supported by the estimate of τ^2 in Table 15, where a value of 0.0 indicates that there was no observed variance between the true effect sizes beyond what would be expected from sampling error alone. Similarly, the I^2 value of 0.0% in Table 14 indicates that no heterogeneity was observed between the studies, implying that all variability in the study findings was attributed to chance.

In the field of data analysis, the use of visual representations is crucial to understanding and interpreting complex information. One such visualization method is the forest plot, which visually represents the random-effect meta-analysis data. Figure 10 illustrates the relationship between the ES of the selected studies and the corresponding parametric data. By examining Figure 10, we can gain more insight into the characteristics of the selected studies, including the measures of homogeneity and heterogeneity.

Analyzing Figure 10, evidence of a tight clustering of data points around the ES value of 0.412. This tightness indicates a high degree of homogeneity among the selected studies, suggesting consistency in measurement and methodology. This finding is reinforced by the homogeneity data presented in Table 15, which provides additional statistical evidence for the uniformity of the selected studies.

A funnel graph is used to assess the presence of publication bias. A funnel plot is a scatter plot that visually represents homogeneity and heterogeneity, explicitly looking for potential biases in the included studies. Figure 11 shows the funnel graph for the selected studies and allows for a visual evaluation of publication bias. By examining the distribution of data points around the central line, we can gauge the presence or absence of bias in the study selection. As seen in Figure 11. The selected studies form the symmetry and tightness of the distribution around the central vertical line. Additionally, the data points were within the dashed lines of the confidence interval. This further supports homogeneity.

Based on these analyzes, the inference was that the relationship of IA with SCR was statistically significant and that the impact was moderate to large. No further investigation was required, given the perfect homogeneity observed in the studies. In general, the analysis provides strong evidence to suggest that the IA has a significant and medium to large impact on SCR.

Table 13

Effect Size Estimate

				Sig. (2-	95% CI		95% PI[a]	
	Effect Size	Std. Error	Z	tailed)	Lower	Upper	Lower	Upper
Overall	0.634	0.0464	13.675	0	0.544	0.725	0.539	0.73

[a] Based on t-distribution.

Table 14

Test of Residual Homogeneity

Chi-square (Q statistic)	df	Sig.
5.275	29	1.000

Tests the null hypothesis that tau-squared is equal to 0.

Table 15

Residual Heterogeneity

Tau-squared	0
I-squared (%)	0
H-squared	1
R-squared (%)	0

Figure 7

Forest Plot IA on SCR

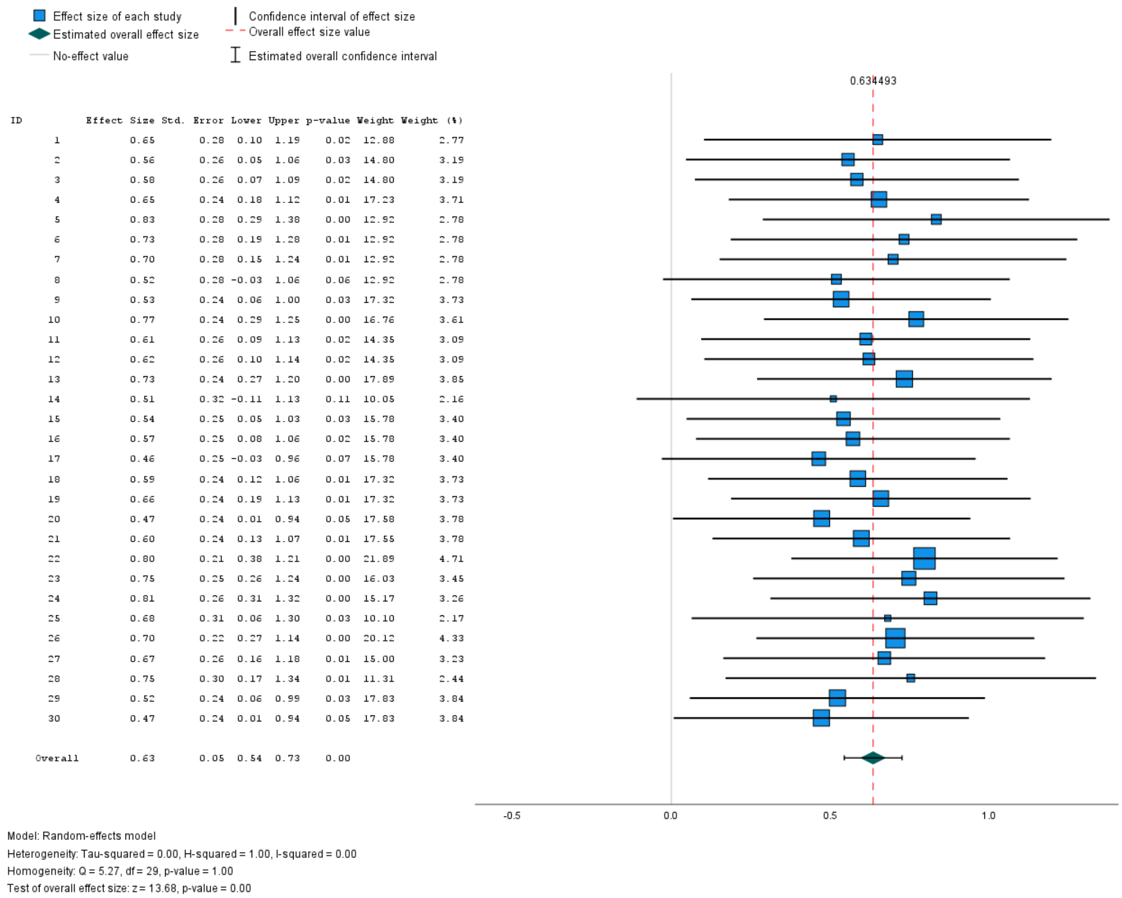
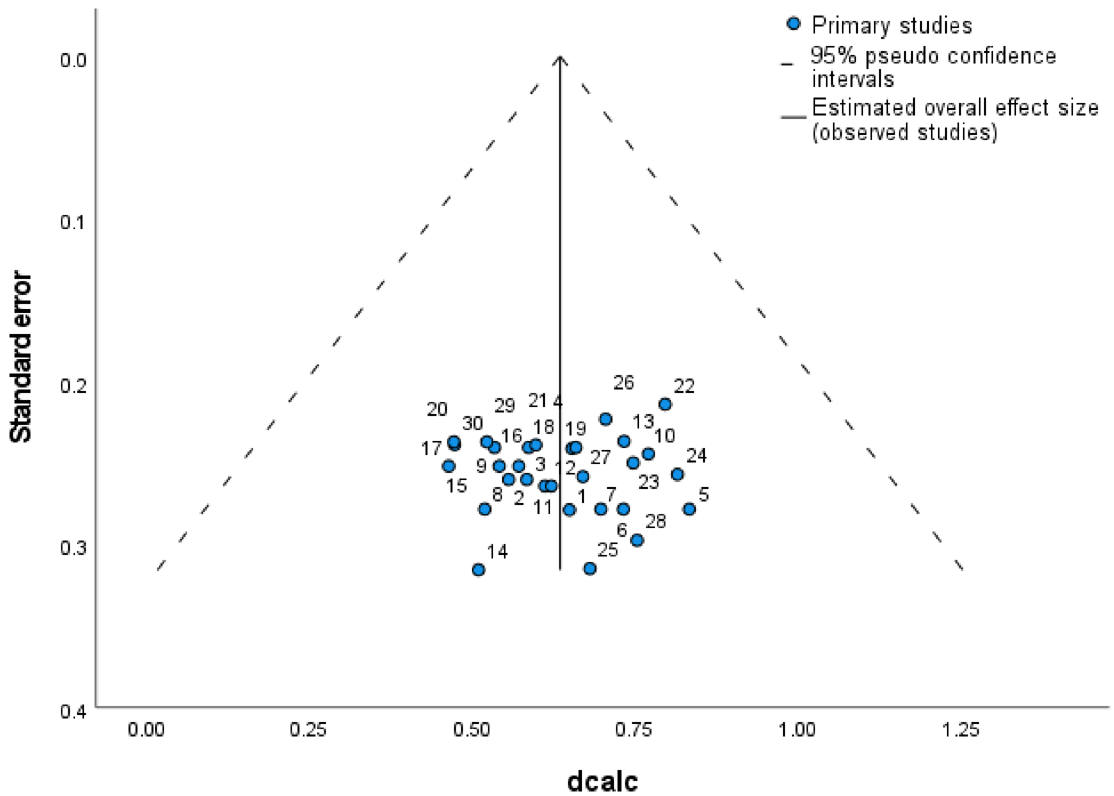


Figure 8

Funnel Plot IA on SCR



In summary, With a d_{calc} = 0.6.34 and p < .001, the H_0 was rejected, and H_1 was accepted, indicating consistency across studies. The studies did not indicate heterogeneity, as evidenced by a Q statistic value of 5.275, df value of 29, p-value of 1.0, I^2 value of 0, and H^2 value of 1.0. Thus, it allows for rejecting H10 and accepting H11, and ES is consistent across studies.

Summary of Analysis

Descriptive statistics are vital in analyzing data from studies. Descriptive statistics were used in this study to assess the impact of COVID on SCR, with a mean effect size (*d*) of 0.36 and SD of 0.09. Cohen's *d* indicated the strength and direction of the effects, with two subgroups, publication year and statistical method, influencing the value of d_{calc}. The forest plot in Figure 4 visually displayed effect sizes and confidence intervals, showing an overall effect size ranging from 0.22 to 0.48, suggesting a small to medium effect with a significant statistical impact ($p < .001$). The confidence interval was narrow, indicating a high confidence level.

Figure 5 was used to assess the normal distribution. Table 5 shows a Shapiro-Wilk test with a *p*-value of 0.075, suggesting not rejecting the null and the data was not significantly different from the normal distribution. Overall, the study used various statistical analyses to understand the impact of COVID on SCR, providing valuable information through descriptive statistics and visual representations. Table 12 indicates that the original research question of statistical relationship could be derived. Data from Table 12, $d_{calc} = .34$ and a $p < .001$, infer a statistically significant positive relationship, thus rejecting the H_0 and accepting H_1. Additionally, the analysis infers that (a) COVID on SCR, $H1_0$, is not rejected, suggesting that ES is not consistent across studies, and (b) IA on SCR, $H2_0$, is rejected, and $H2_1$ is accepted.

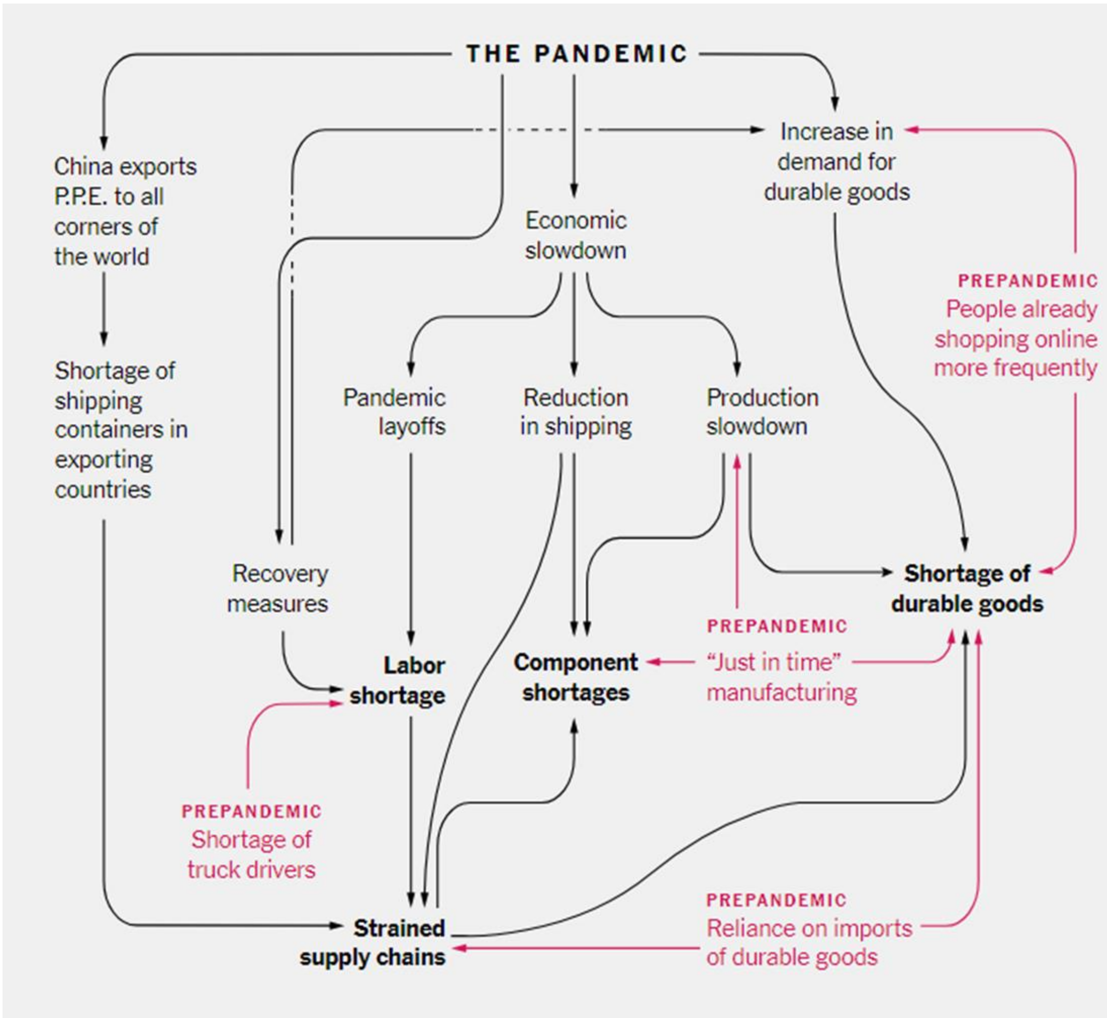
The text presents a descriptive statistical analysis of a study on IA on SCR, including mean, standard deviation, variance, skewness, and kurtosis. d_{calc} measured the effect size of IA on SCR, with a d_{calc} of 0.63 and SD of 0.12. Table 6 highlights the subgroups influencing d_{calc}: publication year, geographical location, and statistical method. RQ1 and RQ2 null $H1_0$ and $H2_0$ cannot be rejected, thus inferring that ES is consistent between studies and the subgroups do not influence the d_{calc}. The distribution of d is slightly negative. A forest plot (Figure 6) visually represents the effect sizes, showing an overall medium to large effect size ranging from 0.46 to 0.83 with a significant p-value. A histogram (Figure 7) suggests a normal distribution assumption, supported by a Shapiro-Wilk test (Table 7) with a *p*-value of 0.420, indicating that the data was not significantly different from the normal distribution.

Theoretical and Literature Conversations of Findings

The COVID-19 pandemic has significantly impacted the global supply chain, causing disruptions and highlighting its complex and interconnected nature, as seen in Figure 12 (Gamio & Goodman, 2021). Businesses have had to adapt their operations to be more flexible and adaptable to ensure SCR (Haraguchi et al., 2023). In response to the dynamic environment created by the pandemic, businesses are now focusing on developing pre-active supply chains to withstand better future catastrophic events (Kähkönen et al., 2021). One promising solution for enhancing SCR is using AI for data mining and leveraging big data, IoT, and corporate knowledge databases (Bag et al., 2021). Business leaders must invest in functional AI nodes to develop adaptive resilience strategies for their supply chains, as these developments were crucial in addressing supply chain uncertainty disruptions and mitigating the impact of global economic collapse (Naseer et al., 2023).

Figure 9

Supply Chain Crisis



Note: From "How the supply chain crisis unfolded", by Gamio, L., and Goodman, P. S., 2021, *The New York Times*. https://www.nytimes.com/interactive/2021/12/05/business/economy/-supply-chain.html

Findings Relate Theoretical Framework

The study employed chaos theory as its theoretical framework, drawing on the works of Lorenz (1993), Maxwell, 1882 Poincaré, 1889; T. Li, 2004; Yorke, 2004; and Ruelle (2020). The findings of the study support the principles of chaos theory. The predictor variables COVID-19 and IA exhibit a nonlinear relationship with the dependent variable, SCR. The results confirm that the association between the predictor and dependent variables was intricate and unpredictable. Notably, this study reveals a strong negative correlation of COVID on SCR and a strong positive correlation of IA and SCR.

Findings Relate Literature

The additional literature search yielded valuable insights that contributed to the overall understanding of the study. Kähkönen et al. (2021) emphasized the emergence of previously unknown vulnerabilities during the COVID-19 pandemic disruptions. It was evident that business leaders were unprepared to handle such unprecedented disruptions. The rapid cascade of disruptions hindered businesses' ability to effectively respond to the dynamic environment of the COVID-19 crisis (Haraguchi et al., 2023).

In terms of SCR, Alvarenga et al. (2023a) proposed that IA integration positively influences SCR. Based on this, Zhao et al. (2023) provided empirical evidence that IA facilitates the development of SCR. Azard et al. (2020) highlighted the role of IA in big data and AI, enabling proactive decision-making processes that improve SCR. Collectively, these findings underline the significance of IA in strengthening businesses' ability to withstand and respond to disruptions, particularly in the context of supply chains. Using IA technologies such as big data and AI, organizations can establish proactive decision loops that contribute to the resilience of their supply chains.

The additional literature search has yielded valuable insights that significantly contribute to the understanding of the study. Kähkönen et al. (2021) highlighted the emergence of previously unknown vulnerabilities during the COVID-19 pandemic disruptions, revealing that business leaders were unprepared to handle such unprecedented disruptions. These disruptions had a rapid cascade effect, hindering businesses' ability to effectively respond to the dynamic environment of the COVID-19 crisis (Haraguchi et al., 2023).

Regarding SCR, Alvarenga et al. (2023b) proposed that the integration of IA positively impacts SCR. This proposition is supported by the empirical evidence Zhao et al. (2023) provided, demonstrating that IA facilitates resilient supply chain development. Azard et al. (2020) emphasized IA's role in utilizing big data and AI to enable proactive decision-making processes that enhance SCR.

These findings underscore the significance of IA in strengthening businesses' ability to withstand and respond to disruptions, particularly within the context of supply chains. By implementing IA technologies such as big data and AI, organizations can establish proactive decision loops that contribute to the resilience of their supply chains.

Applications to Professional Practice

This quantitative study examines the relationship of (a) COVID on SCR and (b) IA on SCR. The COVID-19 pandemic has profoundly impacted the global economy, with the International Monetary Fund projecting a staggering cost of $28 trillion from January 2020 to December 2025 (Elliott, 2020). This ongoing crisis has caused significant disruptions in the global supply chain, necessitating a shift towards reactive supply chain operations. These disruptions have exposed the vulnerabilities inherent in the global supply chain, highlighting the urgent need to mitigate their impact and enhance SCR.

Supply chain leadership in businesses was critical in designing investment strategies to implement SCR. In order to combat disruptions such as the COVID-19 pandemic effectively, business managers must have a comprehensive understanding of SCR and its application in strengthening supply chains (Aman & Seuring, 2021).

Integrating IA into supply chain management has become crucial for decision-makers in devising strategic outcomes to ensure supply chain resiliency (Zhao et al., 2023). The accelerated adoption of IA provides significant benefits in enhancing the overall resilience of the supply chain (Zhao et al., 2023). By enabling faster access to data, IA facilitates four key output pillars: descriptive knowledge of occurrences, diagnostic understanding of causes, predictive analysis of potential outcomes, and perception influencing future events (Ajah & Nweke, 2019).

Ensuring supply chain protection from disruptions necessitates exploring new paradigms (Ali et al., 2021). A critical factor in establishing sustainable supply chains lies in the ability of supply managers across various business domains to develop solutions based on disruption probability (Behzadi et al., 2020; Goldbeck et al., 2020; Jafarnejad et al., 2019; Ribeiro & Barbosa-Povoa, 2018; Scholten et al., 2019). Scholars such as Chowdhury et al. (2019) and Ivanov (2018) emphasized the importance of building tangible and intangible capabilities that effectively combat supply chain disruptions.

This study highlights the significant impact of the COVID-19 pandemic on the global supply chain and the urgent need for enhanced SCR. Furthermore, it underscores the pivotal role of IA in decision-making processes to ensure supply chain resiliency. Supply chain managers can effectively mitigate disruptions and establish sustainable supply chains by adopting new paradigms and developing comprehensive solutions.

Implications for Social Change

The COVID-19 pandemic has undoubtedly caused significant societal disruptions, including supply chains. As researchers have pointed out (He & Harris, 2020), these disruptions have necessitated the adoption of new paradigms in supply chains, aiming to establish new social interaction norms (Ratten, 2020). In this context, businesses must maintain their commitments to Corporate Social Responsibility (CSR) to fulfill their social responsibilities and pave the way for establishing new CSR paradigms (Schwartz & Kay, 2023).

One notable paradigm shift during this crisis was businesses' widespread adoption of teleworking models. This shift has enabled organizations to adapt to the disruptions and made them more resistant to future uncertainties (Turchina et al., 2023). Teleworking has allowed employees to work remotely, reducing the risk of virus transmission and ensuring the continuity of business operations. This approach has proven to be an effective strategy for maintaining productivity and minimizing disruptions.

The COVID-19 pandemic has accelerated the implementation of CSR strategies to stabilize SCR (Svyrydenko et al., 2023). These strategies have focused on reducing job losses by adopting new workforce governance models, ensuring the availability of critical supplies, and promoting economic stability. By actively engaging in these CSR initiatives, businesses have been able to mitigate the social and economic impacts of the pandemic on both their employees and society as a whole.

The findings of this study have significant implications for shaping new social norms during times of disruption. By shedding light on the importance of CSR paradigms and the benefits of adapting SCR, businesses can incorporate these insights into their practices to better prepare for and mitigate the impacts of future uncertainties. Companies that embrace these strategies and effectively incorporate them into their business operations are better equipped to handle disruptions and contribute to society's overall well-being (Baah et al., 2023). By incorporating these insights into their practices, businesses can mitigate future uncertainties' social and economic impacts, shaping new social norms and contributing to a more resilient and responsible business landscape.

Recommendations for Action

In today's rapidly evolving business landscape, staying informed about current trends and recommendations is crucial for success. Recent research in business supply chain leadership has highlighted two key recommendations that can significantly impact organizational performance and resilience. First, businesses must allocate resources to develop adaptive and scalable SCR processes. This allocation was essential to effectively counter the disruptive effects of dynamic uncertainty. By investing in these processes, organizations can enhance their ability to adapt to unexpected changes, ensuring the continuity and efficiency of their supply chains. This proactive approach to resilience can mitigate the negative impacts of disruptions and position businesses for sustained success. The second recommendation was to implement new IA strategies within the decision-making loop. Integrating IA into decision-making involves incorporating adaptive predictive models that effectively analyze and leverage big data and the IoT. By harnessing these technologies, businesses can gain valuable insights and make more informed decisions, thereby improving their operational efficiency and competitiveness in the market.

The findings of this study have the potential to benefit a wide range of stakeholders, including business leaders, corporate boards, government officials, individuals, and educational institutions. The results should be shared through various channels, such as reputable business journals, influential business forums, reputable academic conferences, and relevant government caucuses to ensure widespread dissemination of this valuable information. By disseminating these results, business executives will reevaluate resource allocation and the creation of backup plans in the face of dynamic uncertainty disruptions.

Implementing these recommendations will enable businesses to enhance their resilience and adaptability, positioning themselves for success in an ever-changing business landscape. Allocating resources towards adaptive and scalable SCR processes and embracing IA strategies are crucial actions that business supply chain leadership should consider. By taking these proactive steps, organizations can effectively navigate uncertainties, drive success, and ensure long-term sustainability in today's dynamic business environment.

Recommendations for Further Research

This study investigated the relationship and strength of COVID on SCR and IA on SCR. Through an in-depth analysis, I identified four limitations: reliance on published journals, treating literature data as truth, dealing with the fluctuation of the phenomenon, and relying on free access databases, but these should not undermine the significance and validity of the findings.

For future research, I identified several suggestions: First, it was advisable to include studies without peer review to reduce publication bias and enrich data sources. Second, future research should ensure that articles contain sufficient numerical and statistical data for analysis. Third, investigate the causality between government shutdowns and supply chain failures. Fourth, incorporating data from corporate databases could contribute to the study. Fifth, the COVID-19 pandemic is an evolving crisis, and its impact on IA and SCR constantly changes. Therefore, it is essential for future research to continuously assess and monitor the situation to capture the most up-to-date information. Sixth, investigating the causality between government shutdowns and supply chain failures can provide valuable insights into the impact of policy measures on SCR.

Reflections

While at Walden University, I have encountered challenges and rewards in my academic journey. One significant challenge I faced was finding a sufficient number of articles to ensure the statistical viability of my research. My study focuses on examining the relationship of COVID on SCR and IA on SCR in enhancing the resilience of supply chains. The motivation behind my research stems from observing empty shelves in major consumer commodity stores during the pandemic. This observation sparked my interest in investigating how disruptions such as COVID-19 and technologies such as big data and the Internet of Things (IoT) factor into SCR.

It was essential to acknowledge the pandemic's ongoing and rapidly evolving nature, as this dynamic environment may lead to discoveries that could potentially challenge or negate the findings of my study. Conducting research in such circumstances comes with inherent risks, but it also presents an opportunity to contribute valuable insights to the field.

To address the issue of publication bias, I implemented a rigorous methodology for selecting articles for inclusion in my study. Rather than solely relying on articles that reject the null hypothesis, I consciously included articles that did not reject the null. This approach aimed to mitigate the possibility of biased findings and ensure a more comprehensive topic analysis.

I also recognized the potential for personal bias in my research, particularly concerning my preconceived notions about the visual evidence of a relationship of COVID on SCR. In order to overcome this bias, I established specific inclusion criteria that required the availability or calculability of critical statistical measures, such as *mean*, *number of participants*, and *standard deviation*. This rigorous approach ensures that my study remains objective and reliable.

The primary goal of my study was to contribute to understanding the relationship of (a) COVID on SCR and (b) IA on SCR. While there were potential limitations and biases to consider, I am confident that my study has provided valuable insights into this critical area of study.

Conclusion

The high disruption experienced by Fortune 1,000 companies during the COVID-19 pandemic, as reported by Shrivastav (2022), further emphasized the relevance and urgency of investigating the relationship between these variables. The pandemic has caused significant challenges to global supply chains, resulting in large-scale disruptions and substantial financial impacts on affected companies. Understanding the factors contributing to SCR in such disruptions was crucial for organizations to navigate and mitigate future disruptions effectively.

The random effect meta-analysis conducted in this study rigorously sifted through a substantial number of articles and only those with applicable numerical data. This rigorous approach improves the validity and reliability of the findings. The results of the meta-analysis were COVID on SCR effect size (ES) = 0.345 with a $p < 0.00$, Q statistic = 41.272, df = 23 and a $p < .011$, $I^2 = 49.5$ %, and a $\tau^2 = .003$ and IA on SCR ES = 0.634 with a $p < .001$, Q statistic = 5.275, df = 29, $p = 1$, $I^2 = 0$ and $\tau^2 = 0$ indicates a statistically significant COVID on SCR and IA on SCR with moderate effects. There were indications of heterogeneity in COVID on SCR studies but not in IA and SCR studies. A separated subgroup meta-analysis of year published and statistical method used revealed year published: Q statistic = 97.74, df =23, $p < .001$, $I^2 = 73.4$, and $\tau^2 = .108$ and method: Q statistic = 165.98, df = 23, $p = 0.0$, $I^2 = 91.8$, and $\tau^2 = .435$. The results indicate that the method is the dominant effect of ES.

The disruption experienced by Fortune 1,000 companies during the COVID-19 pandemic, as highlighted by Shrivastav (2022), further underscores the importance and urgency of investigating the relationship of COVID on SCR and IA on SCR. The pandemic has posed significant challenges to global supply chains, resulting in widespread disruptions and substantial financial consequences for affected companies. Consequently, understanding the factors contributing to SCR during such disruptions was paramount for organizations to navigate and mitigate future disruptions effectively.

The findings of this research provide compelling evidence of the significant impact of the COVID-19 pandemic on the resilience of supply chains. A meticulous random effect meta-analysis of 41 carefully selected articles established a moderate to strong relationship between the predictor variables of COVID-19 and IA on SCR. The analysis supports that the research question answered was that there was (a) a significant statistical relationship between COVID and SCR along with a small to medium ES and (b) a significant statistical relationship between IA and SCR along with a medium to large ES exist as established by the criteria in Table 3. Thus, it underscores the existence of a robust positive correlation for both COVID on SCR and IA on SCR. Additionally, The statistical analysis of COVID on SCR does not support rejecting the null hypothesis $H1_0$, establishing that the ES was not consistent across studies and that there were subgroups that influenced ES, thus driving heterogeneity. Additionally, the statistical analysis of IA on SCR supports rejecting H20 and excepting H21, establishing that the ES was consistent across studies and that no subgroups influenced ES.

These results underscore the significance of internal auditing in fortifying SCR during crisis periods, such as the COVID-19 pandemic. Through IA, organizations must recognize the importance of investing in strategies and resources to strengthen SCR. This effort will enable organizations to navigate future disruptions and ensure uninterrupted business continuity effectively.

The findings of this study provide compelling evidence of the substantial influence of COVID on SCR and IA on SCR. The demonstrated correlation of IA on SCR highlights the need for organizations to prioritize enhancing SCR through effective IA practices. By doing so, organizations can better navigate future disruptions and ensure the continuity of their operations.

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Note: References marked with an asterisk (*) indicate studies included in the random effect meta-analysis and documented in Appendix C.

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Appendix A: Permissions to Use

Hi William,

Thank you for contacting me! I grant you the permission to use the diagram.

Best!

Philip

Philip Adu, Ph.D.

Founder, Center for Research Methods Consulting

CENTER FOR RESEARCH METHODS CONSULTING

[redacted]

[redacted]

Author of the book, *A Step-by-Step Guide to Qualitative Data Coding*

Co-author of the book, *The Theoretical Framework in Phenomenological Research: Development and Application*

Composer: *Reflective/Meditation Music*

On Thu, Nov 18, 2021, at 5:15 PM William Ellis <[redacted] wrote:

Dr. Adu,

My name is Bobby Ellis. I am working on a dissertation in Business Administration and would like to use your decision tree from “Very simple way of choosing an appropriate quantitative research design for your study” graphic in my study. The title of my doctoral study is “A Correlation Meta-Analysis of COVID-19 Shock, Intelligent Analytics, and Supply Chain Resiliency”. I need permission from you to use the graphic in my study an email stating this will service for permission.

Very Respectfully

Bobby Ellis

Dear Ellis!

I will be thankful to you, if you will share your work with me...

Usman Zafar Paracha

Sent from Yahoo Mail on Android

On Mon, Nov 29, 2021, at 6:52 AM, Usman Zafar Paracha

[redacted] wrote:

Dear Ellis!

You can use the figure, but kindly give the credit to my book...

I wish you lots of luck.

Usman Zafar Paracha

Search for better treatment of Alzheimer's disease by Usman Zafar Paracha and Amara

Usman Paracha

On Monday, November 29, 2021, 02:18:53 AM GMT+5, William Ellis

[redacted] wrote:

Sir,

I am a doctoral student at Walden University. I wish to use a figure from your book "Basics of Meta-analysis with basic steps in R". The title of my study is "A Correlation Meta-Analysis of COVID-19 Shock, Intelligent Analytics, and Supply Chain Resiliency". In order to do so I will need your permission to use. A response in email to this email will suffice for permission.

Very Respectfully

Bobby Ellis

Appendix B: Descriptions

Table B1

Analytics Variable Description

Variable	Description
Lable	Sequence ID Number
Pub Yr	Subgroup publication year
Meth	Statistical method
Loc	Geographical location
ES	Effect size
d	Cohen's d
d_{calc}	Calculated Cohen's d
SE_{dcalc}	Standard error calculated Cohen's d
d_{sub}	Effect size subgroup
p	Significance
Q statistic	A measure used to assess heterogeneity among study outcomes
Q sig	Q statistic significance value
I^2	Proportion of measure of heterogeneity
τ^2	Estimated variance
H^2	Proportion of between-study heterogeneity propu
t	A measure of statistical significance

Appendix C: Database

Table C1

COVID on SCR Variables Database

Lable	Study ID	Pub Year	Method	Pub Yr	Meth	Study Authors	Yr Pub	n	M-rep	SD-rep	β-rep	t (calc)	d (calc)	SE_d (calc)
1	1	2021	qualitative	1	0	Queiroz et al.	2021	112	5.160	1.570	0.433	5.038	0.480	0.094
2	2	2021	quantitative	1	1	Kähkönen et al.	2021	110	2.470	1.749	0.304	3.301	0.319	0.095
3	3	2021	quantitative	1	1	Kähkönen et al.	2021	110	1.316	1.710	0.235	2.501	0.242	0.095
4	4	2021	quantitative	1	1	Siagian et al.	2021	470	3.374	0.767	0.267	6.001	0.277	0.046
5	5	2021	qualitative	1	0	Nikookar & Yanadori	2021	498	5.290	1.020	0.266	6.725	0.276	0.041
6	6	2021	qualitative	1	0	Nikookar & Yanadori	2021	498	5.700	0.890	0.265	6.698	0.275	0.041
7	7	2021	qualitative	1	0	Nikookar & Yanadori	2021	498	5.860	1.110	0.289	7.357	0.302	0.041
8	8	2022	qualitative	2	0	Robb et al.	2022	227	4.598	1.220	0.428	7.088	0.474	0.066
9	9	2022	qualitative	2	0	Robb et al.	2022	227	4.598	1.220	0.411	7.468	0.451	0.060
10	10	2022	quantitative	2	1	Aigbogun et al.	2022	102	2.810	0.146	0.341	3.627	0.363	0.099
11	11	2019	qualitative	0	0	Gölgeci & Kuivalainen	2019	265	5.720	0.770	0.310	5.288	0.326	0.061
12	12	2019	qualitative	0	0	Wong et al.	2019	203	3.815	0.538	0.230	3.351	0.236	0.070
13	13	2022	quantitative	2	1	Kazancoglu et al.	2022	200	5.370	1.040	0.556	9.424	0.424	0.071
14	14	2023	quantitative	3	1	Hamidu et al.	2023	345	5.890	1.106	0.546	12.070	0.394	0.152
15	15	2023	quantitative	3	1	Alvarenga et al.	2023	290	4.400	1.440	0.400	7.399	0.436	0.059
16	16	2023	quantitative	3	1	Cherian & Arun	2023	220	0.060	1.180	0.426	6.943	0.470	0.067
17	17	2023	qualitative	3	0	Hussain et al.	2023	214	3.951	0.659	0.250	3.759	0.258	0.068
18	18	2019	mixed	0	1	Yu et al.	2019	241	3.820	1.390	0.354	5.852	0.379	0.064
19	19	2023	quantitative	3	1	Hossain et al.	2023	185	3.960	0.347	0.219	3.036	0.224	0.074
20	20	2022	quantitative	2	1	Attig et al.	2022	3132	2.535	1.140	0.343	20.443	0.365	0.018
21	21	2023	qualitative	3	0	Alghababsheh	2023	217	3.960	0.540	0.399	6.384	0.435	0.068
22	22	2022	qualitative	2	0	Todo et al.	2022	1316	1.468	0.833	0.342	13.195	0.364	0.028
23	23	2022	qualitative	2	0	Piprani et al.	2022	191	2.830	0.031	0.431	6.570	0.478	0.072
24	24	2021	qualitative	1	0	El Baz & Ruel	2021	289	0.359	1.708	0.274	4.816	0.285	0.059

Table C2

IA on SCR Variables Database

Label	Study ID	Publish Yr	Geo Loc	Method	Pub Yr	Loc	Meth	Study Authors	Yr Pub	n	β-rep	t (calc)	d(calc)	SE_{d}(calc)
1	1	2022	Ai	qualitative	2	0	1	Iftikhar et al.	2022	166	0.528	8.010	0.649	0.279
2	2	2022	Af	Mixed	2	2	0	Bag et al.	2022	219	0.495	8.426	0.555	0.260
3	3	2022	Af	Mixed	2	2	0	Bag et al.	2022	219	0.494	8.410	0.583	0.260
4	4	2021	Ai	Mixed	1	0	0	Raut et al.	2021	297	0.532	10.828	0.653	0.241
5	5	2021	Ai	qualitative	1	0	1	Bahrami & Shokouhyar	2021	167	0.631	10.511	0.833	0.278
6	6	2021	Ai	qualitative	1	0	1	Bahrami & Shokouhyar	2021	167	0.592	9.492	0.732	0.278
7	7	2021	Ai	qualitative	1	0	1	Bahrami & Shokouhyar	2021	167	0.552	8.548	0.697	0.278
8	8	2021	Ai	qualitative	1	0	1	Bahrami & Shokouhyar	2021	167	0.466	6.810	0.519	0.278
9	9	2020	Eu	quatitative	0	1	2	Zouari et al.	2020	300	0.471	9.248	0.534	0.240
10	10	2020	USA	qualitative	0	1	1	Wamba et al.	2020	281	0.595	12.410	0.770	0.244
11	11	2021	Ai	quantitative	1	0	2	Gu et al.	2021	206	0.541	9.233	0.611	0.264
12	12	2021	Ai	quantitative	1	0	2	Gu et al.	2021	206	0.523	8.807	0.621	0.264
13	13	2021	Ai	qualitative	1	0	1	Cheng et al.	2021	320	0.576	12.605	0.733	0.236
14	14	2021	Eu	qualitative	1	1	1	Hallikas et al.	2021	101	0.451	5.078	0.509	0.315
15	15	2019	none	qualitative	0	2	1	Mandal	2019	249	0.473	8.471	0.541	0.252
16	16	2019	none	qualitative	0	2	1	Mandal	2019	249	0.490	8.870	0.571	0.252
17	17	2019	none	qualitative	0	2	1	Mandal	2019	249	0.411	7.114	0.463	0.252
18	18	2020	Ai	quantitative	0	0	2	Srimarut & Mekhum	2020	300	0.520	10.544	0.586	0.240
19	19	2020	Ai	quantitative	0	0	2	Srimarut & Mekhum	2020	300	0.548	11.347	0.659	0.240
20	20	2021	Ai	Mixed	1	0	0	Yamin	2021	309	0.428	8.325	0.473	0.239
21	21	2023	Ai	qualitative	3	0	1	Lee et al.	2023	308	0.516	10.572	0.597	0.239
22	22	2021	Ai	quantitative	1	0	2	Belhadi et al.	2021	479	0.619	17.249	0.796	0.214
23	23	2023	Global	quantitative	3	2	2	Alvarenga & Oliveira	2023	257	0.595	11.868	0.747	0.250
24	24	2023	NoAMEu	quantitative	3	1	2	Park & Singh	2023	230	0.626	12.174	0.815	0.257
25	25	2022	Eu	qualitative	2	1	1	Cadden et al.	2022	102	0.569	6.988	0.680	0.315
26	26	2022	Eu	qualitative	2	1	1	Laguir et al	2022	405	0.575	14.144	0.704	0.223
27	27	2019	Other	qualitative	0	2	1	Singh & Singh	2019	225	0.559	10.113	0.669	0.258
28	28	2023	Ai	quantitative	3	0	2	Manikas et al.	2023	128	0.602	8.530	0.753	0.297
29	29	2022	Ai	qualitative	2	0	1	Wang & Pan	2022	318	0.463	9.315	0.522	0.237
30	30	2022	Ai	qualitative	2	0	1	Wang & Pan	2022	318	0.427	8.421	0.471	0.237

Appendix D: Exemplar Abstract

Supply managers are concerned that their supply chain resiliency (SCR) might be inadequate to protect their firms' supply networks from sudden disruptions, which could lead to significant cascading failures in their operations. Grounded in chaos theory, the purpose of this quantitative correlational study was to examine the relationships of COVID-19 and intelligent analytics (IA) with SCR. For meta-analysis of published findings, 41 studies published between 2019 and 2023 were selected for this study. The homogeneity test of COVID ES on SCR showed that the average ES was between small to medium size (d = .35), yet not consistent across the studies, $Q(23) = 41.31$, p =.011, $I^2 = 49.52$, $\tau^2 = .003$, $H^2 = 1.982$. Egger's meta-regression results for the effect size of COVID on SCR showed that the studies' publication year was a significant predictor (b = 0.041, t = 3.183, p = .004) while the studies' statistical method was not (b = .011, t = .325, p = .748). Only after accounting for these two study-level characteristics, the ES of COVID was homogeneous across all studies, $Q(22) = 31.120$, $p = .072$, $I^2 = 25.2$, $\tau^2 = .001$, $H^2 = 1.337$. During the same period, the ES of IA on SCR was shown to be, on average, medium size (d = .634) and held consistent across the studies without accounting for any study-level characteristics, $Q(29) = 5.275$, $p = 1$, $I^2 = 0$, $\tau^2 = 0$, $H^2 = 1.0$. A key recommendation for supply chain managers includes developing adaptive and scalable supply chain resilience processes and implementing intelligent analytics to support supply chain decision-making. The implications for positive social change include the potential to provide stable employment opportunities and mitigate the effects of sudden supply chain disruption on consumers and the general public.