THE MEDIATING ROLE OF RISK PERCEPTION IN THE RELATIONSHIP BETWEEN COVID-19 KNOWLEDGE AND STRATEGIC THINKING IN HEALTHCARE ORGANIZATION

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ABSTRACT

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The Covid-19 pandemic has caused significant disruptions across multiple sectors, particularly in healthcare, necessitating the implementation of effective crisis management strategies. This dissertation explores the intricate relationship between Covid-19 knowledge, risk perception, and strategic decision-making among mid-level to executive personnel within healthcare organizations. While existing research has delved into the connection between Covid-19 knowledge and strategic thinking, there is limited understanding of the mediating role of risk perception in the healthcare industry. Employing structural equation modeling (SEM) for data analysis, this study aims to bridge this research gap and offer practical insights for healthcare managers grappling with pandemic challenges. The results affirm the positive influence of Covid-19 knowledge on both strategic thinking and risk perception. Additionally, risk perception is identified as a partial mediator in the relationship between Covid-19 knowledge and strategic thinking. This research enriches the literature by shedding light on the significance of risk perception within the context of Covid-19 knowledge and strategic decision-making within healthcare organizations.

Keywords: *Strategic thinking, Covid-19 knowledge, Risk perception, Pandemic, and Healthcare organizations*

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INTRODUCTION

1.1 Statement of the Phenomenon

There was a worldwide health emergency due to the Covid-19 virus' rapid proliferation. The World Health Organization (WHO) upgraded this epidemic to a pandemic as new cases appear (Kassie et al., 2020). It is crucial to research and comprehend Covid-19 perception and how businesses changed their methods to deal with pandemic conditions in the healthcare industry and other high-risk pandemic-related industries (Khasawneh et al., 2020).

During the Covid-19 emergency, healthcare workers faced multiple obstacles when treating Covid-19- infected patients: preventing the spread of disease, adopting appropriate short-term measures, and constructing long-term plans (Abid et al., 2022). Uncertainties about transmission and disputing assertions on prospective treatment options are all continuing trends in developing new preventative guidelines (Maude et al., 2021). There was also significant amounts of false and misleading information on social media. Therefore, it is not surprising that many people chose and continue to choose not to follow recommendations or precautionary actions. Healthcare organizations continually adjusted their strategies to cope with the impacts caused by Covid-19 (Limbu et al., 2020).

The study will significantly assist healthcare business decision-makers (mid-level and upper-level management) in better preparing for the future regarding marketing performance, improved health services, staying in business without impacting the community negatively, competitiveness, risk mitigation, and profitability. Additionally, there is evidence that recognizing healthcare organizations is essential for following disease prevention measures (Bahurupi et al., 2021). Based on this, knowledge of healthcare organization perspectives can assist in the creation of efficient strategies to avert existing and any upcoming health crises.

1.2 Background of the Problem

The Covid-19 outbreak affected the world and has presented a new level of uncertainty, impacting both lives and businesses. Small and large businesses closed, and communication across business sectors was negatively impacted. Still, as of May 2022, deaths globally had risen to approximately six million plus with total cases of five million plus, while the United States had a global death toll over one million with total cases over one hundred and three million (John Hopkins University, 2023). According to recent research conducted by Nebraska Medicine (2023), the world is currently grappling with a new variant of Covid-19, known as XBB 1.5. This variant has been found to be the most prevalent, accounting for approximately 87.9% of cases. Following XBB 1.5 is XBB 1.9.1, which has been identified in 4.6% of cases. The United States is one of the countries that have been hit hard by this new variant, with an average of 19,508 cases reported daily (John Hopkins University, 2023). Organizational sustainability has been constantly challenged, prompting managers and decision-makers to replan and approach business differently. As a result, organizations have improved their ability to innovate and adapt (Schiuma et al., 2021).

Most organizations, especially small and medium-size organizations, have found it difficult to handle the knowledge gaps about their futures because of Covid-19 disruptions (Al-Faouri et al., 2021). Covid-19 knowledge continues to be important and needed for continual success of organizations. Managers and decision-makers in health-related organizations have been allowed to reduce several health regulations in light of the availability and use of the vaccines after the consequences of the first wave (Maude et al., 2021). Managers with more expertise than their rivals have been able to effectively plan and run their organizations (Penrose, 1980). Better cognitive resource organizations are better able to utilize and grow their resources than other organizations (Zack, 1999). One response to bridge the knowledge gaps was to design an emergent knowledge strategy (Bratianu & Bejinaru, 2020). General behavior theory explores the influence and relationships between knowledge sharing intention and behavior (Yang & Xu, 2021). The social exchange theory has been often used. The social exchange theory explains the relationship between knowledge sharing and behavior. Employee knowledge, especially when shared is among the most significant strategic resources, and the ability to get, integrate, store, share and apply it is essential for building and sustaining competitive advantage (Grant, 1999; Kogut & Zander, 1992). Engaging in knowledge management facilitates an organization's fundamental ability to compete (Zack, 1999).

Communicable disease knowledge and awareness, like Covid-19 and risk perception help motivate people to adopt preventive behaviors (Anderson et al., 2020; Aburto et al., 2009; de Zwart et al., 2010; Lee et al., 2021). Examining and comprehending Covid-19 perception and how businesses have changed their strategies to deal with pandemic risks is important. This research will help explore if there is a knowledge gap in what decision-makers in the health field need to know about future Covid-19, what it is like to implement a proactive strategy, and what the organization currently knows. Considering the gap, a knowledge strategy is needed to help managers bridge the gap and align knowledge resources and capabilities (Zack, 1999). How can decision-makers fill the gap between patients and employees who do not believe in precautionary and preventive measures such as vaccines, wearing masks, social distancing, and rule adherence? Regardless of people's beliefs on Covid-19, through the Department of Labor, the government provided guidance for businesses, to help mitigate and prevent the spread of the diseases in the workplace (United States Department of Labor, 2021).

In simple terms, virtual services may not be able to fully and effectively help people with disabilities, as suggested by Bekele et al. (2020). Healthcare businesses have been able to follow government guidance and also integrate virtual sessions to provide services; however, if the people have physical, mental, visual, hearing, speech, or cognitive disabilities, the reality is that virtual services cannot be fully and effectively provided (Galbraith, 2014).

In healthcare and other pandemic-related, high-risk businesses, it is essential to study and understand Covid-19 perception and how businesses altered their strategies to cope with pandemic risks. Threat appraisal and risk perception are essential factors in the protection-motivation theory needed by decision-makers or business owners to deal with harmful events (Floyd et al., 2000). Decisions can be reactive or proactive to protect from a perceived threat.

Protection-motivation is defined as people responding to stressful or unpleasant life situations and how they make decisions during those times. Making these choices is a means of self-defense against imagined threats (Nudelman et al., 2022). The extremely contagious disease Covid-19 has the potential to infect a large number of people very quickly. The disease's unfavorable effects are severe and linked to mortality as well as immediate respiratory issues (Ezati-Rad et al., 2021). Generally, theories of healthy behavior can assist us in identifying the variables involved in protective behaviors to create programs for health promotion. Rogers first proposed the Protection Motivation Theory (PMT) in 1975, and it has since been widely applied as a paradigm for forecasting protective behaviours. According to PMT, a person's motivation to protect oneself is what determines whether they would engage in a protective behaviour against health concerns (Yu et al., 2022).

The fear appraisal in PMT is to forecast and promote protective responses as well as to explain the mental processes involved in danger and coping appraisals. Threat and coping assessments can result in either adaptive or maladaptive reactions, both of which are regarded as health hazards. Threat assessment in PMT is influenced by the three variables: (1) perceived severity, (2) perceived vulnerability, and (3) perceived benefits of unhealthy behaviours (Ezati-Rad et al., 2021). Perceived severity refers to one's perception of the problem's seriousness (perceived rewards). Therefore, there is a greater incentive to participate in behaviours that promote health if the perceived severity and vulnerability are high and the perceived rewards are low (Elhadi et al., 2021).

1.3 Significance of the Study

This research endeavor aims to provide valuable insights for healthcare industry leaders, empowering them to strategically anticipate and navigate future challenges in the realms of enhanced health services, risk mitigation, and overall financial viability. Compared to other study on how the public perceives danger when taking an infectious disease into consideration, there is less reliable information on risk perception (de Zwart et al. 2009). How the mid- to senior-level manager views Covid-19 can affect business operations. The Health Belief Model (HBM) prevents individual judgments of vulnerability, severity, action obstacles, action benefits, and self-efficacy make up the model's five main constructs (Roy et al., 2020). The Health Belief Model states that managers' attitudes influence the regulations they enact to prevent or lessen the effects of disease or its spread (Li et al., 2020). When faced with a personal threat or risk, people are likely to act, but only if the advantages of doing so outweigh the disadvantages, real or imagined (Kassie et al., 2020).

HBM assumes that the possibility of performing specific health behavior is related to people's belief that they are endangered by certain diseases, their assessment of the severity of these diseases, and the conviction that the target health behavior permits preventing the risk of developing the disease (Sas-Nowosielski, 2016). Managers are faced with workers and patients who, for one reason or another, refuse to take the vaccines or observe the rules needed to curb and mitigate the effect or spread of disease. Considering Covid-19, the model can be applied to convince business owners that the disease may have a social, physical, and psychological impacts on individuals, affecting businesses operations (Sas- Nowosielski et al., 2016).

HBM drove the recommendations for precautions during Covid-19 and discussions of risks involved with the disease should cautions not be followed. The study of risk perception is necessary and relevant with the acknowledgment that beliefs, knowledge, values, and attitudes influence not only decisions but also behaviors (Cori et al., 2020). Generally, people adopt good behaviors to prevent a threat from causing harm when they are aware of it. As a result, risk perception plays a key role in guiding sensible and trustworthy preventative actions, which is a way to counteract the effects of Covid-19 (Iorfa et al., 2020).

Strategy can be defined by identifying four concepts of corporate strategy – portfolio management, restructuring, transferring skills, and sharing activities, these concepts have succeeded in different sectors of business depending on the situation (Porter, 1987). Strategic thinking cannot be accomplished without effective communication, collaboration, problem-solving skills, decision-making skills, managerial skills, and decisiveness (Mbachu et al., 2020). Strategy can achieve sustainable competitive advantage by allowing companies to operate uniquely and differently from others or operate under similar business models differently (Porter, 1987). A strategic strategy assists an organization in becoming innovative during a pandemic by changing and establishing new or modified business models to boost profitability while still serving the target market (Roy et al., 2020). As a result, most businesses have developed strategies and applied management initiatives to respond to the wave of disturbance that Covid-19 has created and use technological tools to manage the knowledge to survive and remain sustainable (Schiuma et al., 2021).

Theoretically, risk perception and Covid-19 knowledge can influence decision-makers in the healthcare sector, especially if risk perception mediates the relationship between Covid-19 knowledge and strategic thinking (Clements, 2020). Healthcare businesses have got to change their business strategies to survive the pandemic. Whether they refocus their efforts on battling Covid-19 or keep a laser-like focus on their core capabilities, each organization handled the crisis differently. Some companies might have seen significant growth when they could use their technology to serve new Covid-19 needs and create new income opportunities. Healthcare organizations that have prospered during the pandemic share various fundamental traits, including using the resources and talents they already have, creating a product or service that is in demand, and being adaptable and flexible to change. To survive the pandemic, healthcare organizations must change their business plans. This study focuses on Covid-19 knowledge and risk perception that could influence strategic thinking among decision-makers in healthcare businesses.

In addition to being susceptible to Covid-19 infection due to frequent contact with ill people, healthcare professionals are also at risk for psychological distress, long work hours, exhaustion, occupational stigma, and physical violence (Maude et al., 2021). As such, they are on the front lines of the Covid-19 pandemic defense. Minimizing that risk is the first step in delivering high-quality healthcare because the health industry has enhanced its ranks regarding the risk it presents to its workers (Kassie et al., 2020).

A healthcare professional's mental health and exposure to this threat may significantly impact how they perceive risk. In order to create a strategy that will effectively prepare health workers for an infectious pandemic, it is essential to analyze their knowledge, attitudes, and behaviors (Ciardi et al., 2021). Managers have to change their organizational practices in reaction to the emergence of this crisis in healthcare settings by, for example, abandoning less urgent medical treatments and other unit operations, creating a safe environment, and providing the best care possible to infected patients. The epidemic has forced healthcare administrators to deal with workloads outside the scope of their duties, abilities, and values, although they are accustomed to frequent and ongoing changes in their everyday lives. Healthcare organizations that have thrived during Covid-19 know risk perceptions, market orientation, innovation, strategic thinking, and their causes and effects.

1.4 Orientation of the Proposed Study

The research is focused on healthcare organizations in the United States. In a crisis, managers are crucial for creating a culture of trust, preserving good communication, and ensuring productivity. Because of this, the success of strategic planning depends on their abilities in a crisis (Arslanca et al., 2021). In addition, middle managers also serve as a crucial hub for the distribution of information through effective communication between top management and field staff (Kassie et al., 2020). Mid-level to senior managers would be the key participants during the study. Research showed that mid-level managers questions current concept of strategy and are proactive by providing top management the opportunity to rationalize and play a crucial role by redefining strategic framework as fast learners (Burgelman, 1983). Covid-19 knowledge, risk perception, and strategic thinking in health organizations are the key areas of knowledge to be developed.

The research will follow a quantitative-method approach. Existing surveys are expected to be used but the exact questions will be selected following the chosen approach and their analysis. Qualtrics and other online sources will be used to recruit 300 participants which will adopt the previous articles on Covid-19 knowledge and risk perceptions (Iorfa et al., 2020) and the antecedents and outcomes of market orientation, innovation, and strategic thinking (Moon, 2013). This quantitative survey will focus on testing the extent to which Covid-19 knowledge serves as an antecedent to strategic thinking in health-related organizations with risk perception as a mediator.

1.5 Summary

In the case of COVID-19, knowledge about the virus and its transmission could influence perceptions of susceptibility and severity (Rosenstock, 1974). At the same time, strategic thinking about reducing risk could be driven by perceptions of the benefits of taking action and confidence in one's ability to take action despite barriers. Risk perception could mediate in this relationship, influencing how people engage in strategic thinking and take action to reduce their risk of contracting or spreading the virus. For example, mid managers and senior managers with higher knowledge about the virus and its transmission may perceive the threat as more severe and themselves as more susceptible, leading to greater motivation to engage in strategic thinking and take action to reduce their risk of infection. Additionally, perceived barriers to preventive actions, such as access to vaccines or personal protective equipment, can influence a business decision maker's risk perception and strategic thinking.

In summary, this research addresses knowledge of pandemics coupled with risk and their impact on strategic thinking in healthcare organizations. Covid-19 knowledge and risk perception could influence strategic thinking among decision-makers in the healthcare businesses, specifically if risk perception is mediating the relationship between Covid-19 knowledge and strategic thinking. Based on this, the research questions are;

1. *How does Covid-19 knowledge affect risk perception in relation to strategic thinking?*

2. *To what extent does risk perception mediate the relationship between Covid-19 knowledge and strategic thinking?*
3. *Is there a significant direct effect of Covid-19 knowledge on strategic thinking, even after accounting for the mediating effect of risk perception?*

This research is important because the outcome should help decision-makers in healthcare organizations better prepare for their adaptation of strategy during emerging crisis situations that affect their organizations. In addition, the research will help researchers better understand the role of risk perception in strategic thinking during a crisis such as Covid-19.

CHAPTER 2

LITERATURE REVIEW

The Covid-19 pandemic had a global impact, added a new layer of uncertainty, and affected people's lives and enterprises. Both small and large enterprises went out of business, and communication between industries suffered. Knowledge of Covid-19 is still crucial and required for a business to succeed moving forward. Due to the availability, managers, and decision-makers in organizations that deal with health have been permitted to relax some health requirements. Implementing an emergent knowledge strategy was one way to close the knowledge gaps. The influence and connections between information-sharing intention and conduct are examined by general behavior theory. Social exchange theory has been applied frequently. The social exchange theory explains the connection between behavior and knowledge sharing.

One of the most important strategic resources is employee knowledge, especially when it is shared, and the capacity to acquire, integrate, store, share, and apply it is crucial for creating and maintaining a competitive advantage. Knowledge management activities help an organization's core competitiveness. HBM assumes that the possibility of performing specific health behavior is related to people's belief that they are endangered by certain diseases, their assessment of the severity of these diseases, and the conviction that the target health behavior permits preventing the risk of developing the disease.

2.1 Covid-19 Knowledge

Data on knowledge, attitude, and preventative measures were critical to developing successful protective actions and controlling the incident of Covid-19 (Vuong et al., 2022). Covid-19 knowledge would be crucial in determining the strategies to prevent the virus's spread (Bahurupi et al., 2021). During the Covid-19 emergency, healthcare workers have faced multiple obstacles when treating Covid-19 patients: preventing the spread of disease, adopting short-term measures, and constructing long-term plans (Abid et al., 2022). Emotional exhaustion among Health care workers resulted in medical errors, a lack of empathy when dealing with patients, decreased productivity, healthcare worker illness, and increased turnover (Hoyos-Vallejo, 2021). Strategies and critical thinking enhanced productivity among healthcare workers throughout the epidemic by lowering emotional stress among employees (Temsah et al., 2020). When making decisions on employee welfare, healthcare organizations should take the psychological stress into account because it will increase their revenues (Gorini et al., 2020).

Approximately 278 medical doctors and healthcare specialists died during the pandemic's first wave, with 44% based in Italy (Gee & Skovdal, 2017). This effect on the medical sector demonstrated a gap in knowledge concerning the virus transmission mechanisms and available prevention and treatments for those affected. The Covid-19 cases among healthcare professionals were documented in studies in China (4.4% of all cases), including 23 fatalities that may have been barred in Covid-19 cases (Shahul

Hameed et al., 2021). About 13% to 14% of Covid-19 cases were confirmed and reported cases in different parts of the world (Steptoe-Warren et al., 2011). To prevent and limit the effect of Covid-19, the World Health Organization (WHO) developed and recommended preventive and health procedures for the global health sector, which can affect about 10% of HCPs due to Covid-19 (Yang & Kim, 2022).

People may share their information, experiences, and talents (Kassie et al., 2020). Covid-19 related knowledge sharing is a resolute act of communication amongst healthcare practitioners (HCPs) to communicate pandemic information internally and beyond the healthcare organization (Mbachu et al., 2020). Knowledge sharing and information exchange are critical for healthcare workers to deliver safe, effective, and quality patient care during a pandemic (Saqlain et al., 2020). Covid-19-related information sharing also increased group interaction, connections, and performance to address Covid-19 patient requirements (Roy et al., 2020). Effective Covid-19 information-sharing practices provided healthcare organizations with a competitive advantage in making evidence-based clinical decisions. As a result, it was critical to create Covid-19-free populations (Graf-Vlachy et al., 2020).

A person's access to Covid-19 knowledge is more important than their amount of formal education (Lee et al., 2021). Moreover, higher vaccination acceptance is linked to accurate understanding about Covid-19 and connections with persons who had the virus (Clements, 2020). People who are committed to community health and have a better understanding of the impact of preventative actions are also more likely to be vaccinated

(Bhagavathula et al., 2020a). Instead of considering how the vaccination will impact their personal life, the senior-level manager or leadership's understanding of Covid-19 appears to be influenced by their concern for the community (Miller et al., 2021). Covid-19 had a major impact, PPE use and compliance with social distancing were both consistent with a perception of a high-level threat (Alrubaiee et al., 2020).

The effect of Covid-19 knowledge seems depend on the people’s awareness, attitudes, safe practices, as well as the acceptability of vaccines. Considering Africa, the often-poor healthcare systems are understaffed, have poor knowledge-sharing, and are unable to acquire vaccines in a timely manner (Abdel Wahed et al., 2020; Alrubaiee et al., 2020; Elhadi et al., 2021). Further, the chance of managing the Covid-19 pandemic depends on vaccination uptake and acceptance of the Covid-19 vaccine. Confidence is critical, and measures to reduce public skepticism for vaccination is difficult (Clements, 2020).

During the Covid-19, a recent study offered early evidence of managers' mental health and its determinants. Managers, or those in charge of making choices and directing people, are generally thought to be more vulnerable to mental health problems (Graf-Vlachy et al., 2020). Managers may suffer more mental breakdowns during the Covid-2019 pandemic, as they unable to manage as expected and may be under pressure to execute their duties such as budget cuts or staff layoffs (Kassie et al., 2020; Li et al., 2020; Maude et al., 2021). Only the board of directors of health organizations may directly relate worker layoffs to mental health problems (Clements, 2020). The military and emergency services are two professions that have been identified as having a significant risk of employee mental illness (Kassie et al., 2020), primarily as a result of frequent exposure to potentially traumatic incidents. These professional groups offer the perfect setting for investigating the possible influence of organizational and leadership characteristics of mental health outcomes (Miller et al., 2021).

The Covid-19 outbreak has been shown to be a complex phenomenon, despite first being seen as primarily a threat to public health care systems (Saqlain et al., 2020). It appears to have impacted and changed several aspects of everyone’s' lives, including public transportation and educational institutions (Gorini et al., 2020). Moreover, one of the most significant developments brought about by the Covid-19 epidemic relates to the commercial sector where the governments enacted rules, prohibitions, and limits as the Covid-19 pandemic expanded to stop the virus's spread (Adachi et al., 2022).

According to the Mbachu et al. (2020), Covid-19 knowledge and risk perception influence strategic thinking among healthcare decision-makers and examined whether risk perception is a mediating element in the relationship between Covid-19 knowledge and strategic thinking. The study investigated whether risk perception is a mediating factor in the link between Covid-19 knowledge and strategic thinking, especially how Covid-19 knowledge and risk perception may affect strategic thinking among healthcare decision-makers. Due to how pandemics impact many businesses, it is essential to understand the Covid-19 perspective and how businesses altered their strategy to deal with the pandemic crisis (Maude et al., 2021).

Managers need to understand how to unlearn some practices since businesses need to survive in unpredictable circumstances (Chereka et al., 2022). According to the Vuong et al. (2022), healthcare worker are frequently exposed to job-related risks under regular circumstances, these risks are more obvious in an emergency situation. These dangers include sickness, fatigue, pressures from family and friends, and mental and physical health. However, exposure to infection and mental health are the two main concerns of greatest concern during a pandemic (Maude et al., 2021).

2.2 System Theory and Covid-19

The Covid-19 pandemic has significant human, social, and financial repercussions. Effective control measures must be put in place in order to initially reduce and ultimately control this unique virus, particularly in countries with limited resources. Considered a paradigm shift in human thought is systems thinking. It first emerged in the field of business and management but has since spread to all disciplines or "systems," particularly when the human element is a crucial component, as in social systems (Hassan et al., 2020). General system theory, which emerged in the 1940s through the efforts of biologist Ludwig von B., aimed to provide a fresh approach to the examination of life and living systems while also serving to tackle the growing intricacy of global issues (Bahari et al., 2021).

Before the Covid-19 crisis, the systems thinking method had previously been used to address issues with public health (Naamati-Schneider, 2020). According to the Hassan et al. (2020), Systems theory in Health care is regarded as a system since it is an entity made up of interconnected and dependent pieces that work together to accomplish a common goal. The idea of various layers of component dependency is at the heart of it (Parikh et al., 2020). Any modification to one component of the system has an impact on both that component and the entire system. Strong-leverage locations are regions where system interventions have a greater impact (with an equivalent input) (Vuong et al., 2022). According to systems thinking, Covid-19 outbreak has so vividly highlighted how interconnected all of the health systems (Graf-Vlachy et al., 2020). The Covid-19 epidemic had unanticipated effects on every aspect of life, including the business, entertainment, transportation, and education. The domain of "unintended consequences" was also emphasized as another crucial area in the Systems Thinking perspective (Roy et al., 2020). The Covid-19 outbreak has so vividly highlighted how intertwined our systems are.

The Covid-19 epidemic had unanticipated effects on every aspect of life, including business, entertainment, transportation, and education (Kassie et al., 2020). Moreover, the accompanying effect of trying to circumvent Covid-19 resulted in unforeseen problems, which is also an important area in the System Thinking perspective. For instance, to mitigate the risk of covid-19, the government and the states put in mandatory curfews, business closures, etc., forcing most people to stay home or work from home. These resulted in increased mental health problems, family problems, and health care issues (Nudelman et al., 2022), and the individuals affected also include organizations, mid-level managers, to senior-level managers.

The systems thinking method directs management and healthcare professionals (Mont et al., 2021) on how to manage services during a medical emergency while keeping in mind both the quality (Li et al., 2020) and safety of healthcare services being provided to patients as well as the well-being of personnel (Saqlain et al., 2020). Using systems thinking is a comprehensive approach to better understanding how system components interact with one another through time, the causes of system flaws, and the best strategy for an intervention that solves problems in a highly effective way (strong leverage areas) (Elhadi et al., 2021). An in-depth comprehension of system dynamics is made possible through systems thinking (Mont et al., 2021). Primarily, a thorough grasp of the system complexity that underlies health issues is necessary for improving health (i.e., causes of issues and ways of solving them) (Huynh et al., 2020). The following steps are crucial to systems thinking: Root cause analysis, choosing and concentrating on high leverage areas, redesigning the system, taking steps to mitigate any unintended repercussions of these interventions, and continuously learning and improving as a result of the entire process (Hassan et al., 2020).

Even though the most technologically advanced countries of the world have struggled with the impact of the effect of the virus, , it is unknown how Nigeria, with a friable and underdeveloped healthcare system, stands a chance in combating and stopping the disease from spreading among its densely populated and already vulnerable populations (Islam et al., 2020). With no proven and acceptable pharmaceutical cure, the best way to curb the virus and prevent it from spreading may be to adopt precautionary behaviors (Maude et al., 2021). Adopting cautious behaviors has shown to be the most successful method of preventing the spread of illnesses worldwide, mainly when vaccinations are not yet readily available (Mont et al., 2021). However, the difficulty arises when determining how much people are aware of the contagious illnesses and if this information will result in preventive action (Ciardi et al., 2021).

During the Covid-19, conspiracy theories proliferated quickly, claiming that Covid-19 was a part of an international biowarfare program (Hoyos-Vallejo, 2021). Belief in conspiracy theories reduces pro-health behaviors and support for public health measures, even in the aftermath of prior epidemics (Naamati-Schneider, 2020). To develop Covid-19 preventive and treatment methods, researchers must first understand the effects of conspiracy theories on pro-health behaviors and policy support. Conspiracy theories, particularly pertinent to the Covid-19 epidemic, serve an existential goal by making individuals feel safe in their surroundings (Savadori & Lauriola, 2021).

Knowledge is a fundamental component of human existence, and deficiencies in knowledge result in mortality in circumstances like Covid-19, claim Shahul-Hameed et al. (2021). There is a gap in knowledge that could impede HCWs from understanding the illness's nature (90%), common symptoms (82.8%), mode of transmission (85.7%), and preventative measures (97.1%). However, only 72.3% of respondents were aware of the Covid-19 incubation time (Limbu et al., 2020). As a result of the difficulty of dealing with the pandemic work schedule, there is a significant knowledge gap that might encourage HCWs to violate the rules of isolation (Kassie et al., 2020). The significant knowledge gaps are likely caused by a lack of training programs for HCWs as well as a lack of scientific updating at the individual and community levels (Elhadi et al., 2021). The pandemic work schedule puts a strain on HCWs, so administrative authorities must step in to make sure HCWs receive regular training (Maude et al., 2021).

2.3 Risk Perception

Risk perceptions are subjective ideas about possible sources of harm or the likelihood of losing money (Ciardi et al., 2021). Perceived risk has three components: perceived likelihood (the possibility that one would suffer harm from the hazard), perceived susceptibility (a person's inherent susceptibility to a hazard), and perceived severity (the extent of harm a hazard would cause) (Graf-Vlachy et al., 2020). Stressful work environments are also perceived as risky such as those of HCWs in the pandemic.

In terms of healthcare clients, risk perception may follow negative occurrences such as natural catastrophes and pandemics (Kassie et al., 2020). The degree of risk people believe they face from the ongoing Covid-19 pandemic is critical in determining whether they comply with better health measures designed to lower the number of new infections (Abu et al., 2021; Mont et al., 2021). Risk perception plays a role both as a factor that influences people's mental health and as a tool that aids in preventing exposure to the novel coronavirus (Ciardi et al., 2021). Although it is not surprising that a pandemic might lead to issues with both physical and mental health, understanding how people react to Covid-19 and protect themselves from it can help us better understand how to manage the outbreak (Elhadi et al., 2021). People's views of the Covid-19 risk have a big influence on how they manage their mental health during the pandemic and whether or not they take precautions and engage in preventative actions (Graf-Vlachy et al., 2020).

During the initial pandemic stage, the risk perception is low because people are unfamiliar with the situation (Parikh et al., 2020), wellness, and immunization characteristics, as well as their sources of information about Covid-19 and how much they trusted them, were statically significantly linked to WHO perceptions of the risk of infection and severe illness (Abu et al., 2021). Therefore, decision-makers did not think strategically at the initial stage because they did not have enough knowledge to perceive risk (Singh et al., 2022). For better risk perception, using effective sources of information from WHO was essential because it affected the decision-making process (Adachi et al., 2022).

A variety of factors influence an individual's perceptions of and reactions to dangers. Individual's values, beliefs, attitudes, and broader social or cultural ideals or dispositions impact how dangers are seen or accepted (Earnshaw et al., 2020). Moreover, a more thorough awareness of dangers will not result in a consistent reaction. Understanding qualitative risks and advantages is only one component of effective risk perception; prior experiences and beliefs also play a role in the process (Elhadi et al., 2021). People who distrust the government or large businesses in general, for instance, may be less likely to accept the vaccination risk estimations provided by government health authorities or vaccine producers (Bekele et al., 2020).

Healthcare professionals' understanding about the use of face masks in disease prevention was modest to inadequate at the beginning of the pandemic (Saqlain et al., 2020). HCWs, pharmacy workers and nurses had a considerably greater degree of awareness regarding Covid-19 transmission routes, symptoms, and therapy (Saqlain et al., 2020). Reducing the risk of Covid-19 in delivering high-quality health care because the health sector faced a higher rate in terms of the risk the pandemic posed to workers (Chereka et al., 2022).

More preventative activities and adherence to official guidelines were inferred by a greater Covid-19 risk perception. Additionally, when it came to influencing one's perception of risk, having a chronic illness or believing that one's health is poor, being frequently exposed to Covid-19-related news, looking for information about the virus, coming into contact with it, having social trust, being inclined to get immunized, and being a Democrat all showed a positive correlation (Huynh et al., 2020; Lee et al., 2021). In health officials' opinion, systematic testing is essential when choosing whether establishments and other locations should be open or shut (Clements, 2020).

Risk analysis converts technical information into understandable language. Risk analysis needs extensive training and expensive resources to be completed to a publishing quality (Parikh et al., 2020). However, even quick computations may be used to help people make sense of otherwise perplexing options. Risk analysis can assist in explaining why rational individuals occasionally make divergent judgments when combined with behavioral studies (Vuong et al., 2022).

Although some studies have shown more scores in risk perception among the male counterpart than females, where the gender effect on risk behavior is partially mediated by risk propensity (a predisposition to risk), this new insight tends to show that risk perception could assume any direction, depending on the potency of other underlying variables (Savadori & Lauriola, 2021). Moreover, some variables such as the greater perceived likelihood of adverse outcomes have been found to partially mediate females' lower propensity toward risk choices in gambling, recreation, and health domains, as well as the tendency of women to be more risk averse than men (Shaik & Dhir, 2020).

2.4 Health Belief Model (HBM)

The health belief model (HBM), which is utilized as a conceptual framework and a theoretical road map for health behaviours, is the most frequently offered model to explain the elements influencing the behaviour. Health belief models state that people's risk perceptions affect their willingness to follow advised safety precautions (Limbu et al., 2020). According to the HBM, the probability of a person adopting acts to improve their health can be predicted by their belief in their risk of contracting a disease or condition (Limbu et al., 2020). Perceived susceptibility, perceived severity, perceived benefits, perceived barriers, perceived self-efficacy, which relates to one's degree of confidence (Graf-Vlachy et al., 2020), and impulses to behavior, which motivate people to adopt preventive health practices, are the six core constructs that make up the HBM model (Bekele et al., 2020). For instance, those who perceive their risk of developing a disease are more likely to want to be vaccinated against it (Islam et al., 2020). Many models that explain behaviors connected to health-related choices include risk perception at their core (Elhadi et al., 2021).

All of these constructs are influenced by a person's background, and the type of information that person holds mediates how likely they perceive themselves to contract the coronavirus. These factors untimely could affect a person's emotional and behavioral responses to Covid-19 and can help to explain why a person chooses to practice preventive health. The HBM suggests that people's beliefs and attitudes about a health threat and their perceptions of their ability to take action to reduce the threat influence their health behaviors. Specifically, the model proposes that perceived susceptibility to a threat, perceived severity of the threat, perceived benefits of taking action to reduce the threat, perceived barriers to taking action, and self-efficacy for taking action all affect health behavior. A complete model is provided, and the explanatory power of the model is empirically verified using a set of highly reliable measurement constructs on a nationwide sample of the Italian population during the Covid-19 emergency epidemic (Bhagavathula et al., 2020b).

Senior level managers or leadership awareness of the virus and the lack of a specific treatment or prescription for the illness may have reduced people's desire to take precautions (Lee et al., 2021). The fact that many beliefs regarding the nature and origins of the pandemic are largely unsupported by evidence also had an impact on how individuals took precautions (Maude et al., 2021). Therefore, issues related to precautionary health behavior in populations have been linked to individuals' belief systems and how they perceive fear or risks of contracting a Covid-19 disease. Therefore, the health belief model (HBM), may offer explanations for the failure of the Nigerian people to adopt disease prevention strategies and screening tests for early detection and curbing the spread of the disease. Each of the six HBM components and the practice of cautious behaviour has a significant correlation (Mont et al., 2021).

People started practicing preventive behaviours early because they thought their symptoms were more severe (Huynh et al., 2020). A person is also more likely to take preventative healthy behaviours seriously if the consequences of contracting Covid-19 (such as hospitalization, pneumonia, and death) are severe, according to the perceptions of susceptibility and severity (Lee et al., 2021). Specifically, the HBM proposes or suggests risk (threat) perceptions (perception of susceptibility to disease and perception of the severity of the disease) as essential elements (channels of influence) that help in predicting individual health-related behaviors (Mbachu et al., 2020). Several elements, such as socioeconomic, psychological, and educational components, can affect vaccine resistance. Major predictors of Covid-19 vaccine reluctance include people's health beliefs (Kassie et al., 2020). One of the most popular models for analyzing vaccination behaviour against Covid-19 is the Health Belief Model (HBM). In order to determine whether risk perception may serve as a mediator between Covid-19 knowledge and precautionary behaviours, this study used HBM to examine how Covid-19 knowledge and risk perceptions could impact precautionary behaviours (Mont et al., 2021).

2.5 Risk Perception Theory

According to the risk perception theory, distinct emotions like fear and rage have quite varied effects on how one perceives risk. For instance, fear is a low certainty and control emotion that results in negative risk perceptions, but fury is an emotion with a high degree of confidence and control (Parikh et al., 2020). The understanding of how people and societies react and respond to risky situations can be supported by the notion of risk perception (Earnshaw et al., 2020). According to research on risk perception, people do not choose which hazards to focus on, dread, or avoid based on a straightforward objective assessment of probability (Khasawneh et al., 2020). On the other hand, risk perception is an abstract and socially created phenomenon, and reactions to risk occurrences are sometimes impossible to predict little dangers may be exaggerated to excessive proportions, while other, more lethal threats may be largely disregarded (Singh et al., 2022).

The severe acute respiratory syndrome (SARS) is a virus that affects people' respiratory systems. It mutated as it moved from animals to people. Coughing, sneezing, and close contact all seemed to be effective SARS transmission methods (Temsah et al., 2020). The infectious outbreak had flu-like symptoms such as fever, coughing, chills, exhaustion, and shortness of breath, headaches, and diarrhoea (Vizheh et al., 2020). A specific risk occurrence interacts with psychological, social, and cultural processes to enhance or decrease risk perceptions (Chereka et al., 2022). The characteristics of the risk event itself, particularly how "dreaded" and "unknown" they are, as well as how it is interpreted and expressed by social actors like downstream systems (Islam et al., 2020), historical, social media, or the government, are among the factors that influence risk perception that is helpfully highlighted by SARS (Maude et al., 2021).

One understands and reacts to these socially manufactured danger signs depending on their attention filter, personality attributes, and attitudes (Adachi et al., 2022). Furthermore, how a person perceives risks is influenced by cognitive heuristics, which are collections of inferential principles that individuals use to make decisions under unclear circumstances (Spicer, 2020). The "affect heuristic," for instance, illustrates how emotional responses to risky events can intensify or decrease feelings of danger as well as how quickly emotional impressions precede and guide risk evaluations (Shahul-Hameed et al., 2021). Perceptions of danger in unknown circumstances can be significantly influenced by emotions, trust, and intuition (Hoyos-Vallejo, 2021). For instance, people with optimistic risk perceptions about an impending threat and strong dispositional optimism may be more inclined to downplay the seriousness of the threat and less likely to seek out additional medical information (Roy et al., 2020).

The processing of risk cues at the societal and individual levels influence behavior and decision-making (Naamati-Schneider, 2020). On a societal level, a "ripple effect" of risk perceptions can cause fear, stigmatization, and aversion behavior to spread widely across geographic, temporal, and sectoral borders, having a considerable impact on people's lives in terms of politics and economics (Zięba, 2021). Risk perceptions are influenced by both objective facts and knowledge about past events. For instance, engaging in risky actions is linked to suitably greater risk perceptions, while taking precautions results in a subsequent, appropriate reduction in risk perception (Mont et al., 2021).

Risk perceptions from people's cognitive and emotional perspectives, as well as a more encouraging role of news media in the process (Graf-Vlachy et al., 2020). Explaining the mechanisms by which news and entertainment media influence risk perceptions, Khasawneh et al. (2020) discovered that: (1) exposure to news media is positively correlated with the cognitive dimension of risk characteristics, whereas exposure to entertainment media is positively correlated with both their cognitive and emotional dimensions; (2) the emotional, but not the cognitive, dimension of risk characteristics is positively relatable to exposure to news media (Limbu et al., 2020). People may believe they are more likely to contract a disease, for instance, if a family member has already been diagnosed with it. Additional relevant information also contributes to the establishment of risk perception, even though elements like family history may provide some useful data regarding actual illness susceptibility (Parikh et al., 2020). For instance, the frequently with which a risk is shown in the media has a significant impact on how people perceive risk. To have a stronger insight of how source, medium, message, risk/crisis type, and audience characteristics interact to affect the senior-level manager or leadership’s risk perceptions (Elhadi et al., 2021) and subsequent behaviours, more serious theoretical and empirical efforts should be made to integrate social media research across disciplines (Chereka et al., 2022). Risk communication can be improved through educating the people and encouraging them on how to follow advised actions (Elhadi et al., 2021).

2.6 Strategic Theory

Strategic thinking is a deliberate and logical thought process that concentrates on evaluating key elements and variables that will affect a company's long-term performance (Mont et al., 2021). Strategic thinking encompasses the purposeful and cautious prediction of threats, weaknesses, and opportunities. Ultimately, the outcome of strategic thinking and analysis provide a distinct set of strategies and objectives for a company to endure. Strategic thinking typically considers competition, customer wants and needs, new entrant threats, economic pressures, and resource availabilities (Porter, 1987; Saqlain et al., 2020). Companies who make and execute strategies perform better (Adachi et al., 2022). Knowledge affects an organization's thinking because if managers do not know the strategy, its implementation will fail (Shaik & Dhir, 2020).

The healthcare system is no exception to the general norm that complex systems tend to be conservative and somewhat resistant to change. The difficulty is that any strategy that does not include doctors as key players in the healthcare revolution will fail (Sturges, 1994). Recognize that effective communication of corporate strategy, ensuring that enterprise-level plans are reflected in the plans of the various departments of an organization, carrying out strategic initiatives to carry out the overall plan, and coordinating competency development plans, personal goals, and incentives of employees with strategic objectives are all necessary for effective strategy execution (Mont et al., 2021).

Middle-level managers are a crucial conduit and point of contact for supporting service departments and a link between senior management and operational staff. In actuality, managers are positioned vertically and horizontally in the organization's center (Maude et al., 2021). One of their primary responsibilities is interpreting and then communicating the established strategies into management choices and business action. The organization's senior management views middle-level managers as the implementers and information providers of their decisions (Mbachu et al., 2020).

Hence, inside an organizational department like production, quality control, marketing, finance, and research and development, this group of executives is in charge of carrying out the second-level executive functions (Mont et al., 2021). Implementing the organizational goals established by senior management, which include allocating resources, getting in touch with other departments, and overseeing departmental operations, demonstrates the significance of intermediate-level managers. The primary distinction from other management levels is the integration of operational and senior management expertise (Nudelman et al., 2022). In order to receive orders from senior management and comprehend how those orders are carried out and evaluated, middle-level managers must be close to the operational staff and top management. This combination can mediate between the organizational strategy and the operational actions (Singh et al., 2022).

Middle-level managers are significant in strategic management as a group that participates in competitive strategies and seeks to outperform the creation of fundamental strategies (Limbu et al., 2020). In other words, middle-level managers are the new breed of strategists caught between operational effectiveness and competitive strategies. For middle-level managers, there are three main definitions and descriptions. However, even though they are all significant, they need to represent middle-level managers adequately (Lee et al., 2021).

The nature of this successor role was very transactional: middle managers would take the strategic directives and instructions from executives, translate them into specific tactics, and then communicate those tactics to the individual contributors—that vast array of resources at the business end of the organization (Yu et al., 2022). The nature of organizational transformation is changing, which is why middle managers—project managers, program managers, resource managers, or directors of project offices- are challenged to perform different roles (Vizheh et al., 2020). Until a relatively recent time, internal and external changes that affected businesses were singular, one-time phenomena. Middle managers, or mid-level leaders, have a fundamental responsibility to assist others around them in shifting from an extrinsic (compelled) to an intrinsic (desired) perspective on change (Roy et al., 2020).

Undoubtedly, a piecemeal strategy will fail. Focusing on shared objectives while using motivational strategies such as peer pressure, shared purpose, performance measurement, and strengthening a patient-centered approach are necessary to involve doctors who can be seen as decision makers in system transformation (Galbraith, 2014). The organizational mission, aspirations, and goals must be made clear as the first stage in any strategic transition. The mission of an organization states its unique purpose or reason for existing. The organization's leaders' desired outcomes are reflected in the organization's vision as it carries out its goal. The company pursues its broad strategic goals in order to carry out its mission (Miles et al., 1978).

The organization must plan and think strategically during a pandemic to stay alive. Most organizations do these things as part of how they handle strategic management. Strategic thinking needs strategic planning (Shahul-Hameed et al., 2021). Planning, which comprises analysis, entails actions and checks used to develop, include, and pay attention to competing strategies. In other words, strategic planning is about thinking strategically or setting strategies (Gorini et al., 2020). The project management process includes planning, communicating, coordinating, adapting, and managing resources. The project's scope, timing, cost, quality, and resources must be determined and balanced. There are two different project management methods: agile and traditional (Ciric et al., 2019).

In traditional and agile management, the project manager supervises and keeps track of the project. They make decisions to keep the project on course and achieve its objectives (Maude et al., 2021). Risk, quality, and change management are also necessary for both strategies. With that said, let us examine the distinctions and parallels between agile and traditional project management and how they stack up against one another

(Bratianu & Bejinaru, 2020). Agile Management Certification prioritizes teamwork, customer collaboration, and flexibility, while a traditional system emphasizes upfront planning where variables like cost, scope, and time are given weight (Flood et al., 2016). During each iteration of a software development project, this iterative strategy focuses more on incorporating client feedback and continual releases (Abdalla et al., 2022). During the Covid-19, business owners who were not proactive in their approach or methods went out of business. Healthcare organizations can evaluate their processes and policies to become more proactive in their business strategy (Mont et al., 2021).

Covid-19 is a problematic situation and difficult to survive; healthcare organizations can adopt specific and proactive measures to stay ready for such a jolt. Management must continue operations despite poor financial situations (Gee & Skovdal, 2017). Management and decision-makers adapt to changing circumstances, including changing the hospital's strategic plan (Gorini et al., 2020). Strategic planning and thinking support achieving multiple goals. Efforts to respond to pandemics make strategic initiatives rely on healthcare resilience. In an unpredictable era, corporate strategy transformation may be required for healthcare organizations to remain robust (Abid et al., 2022).

Systems-thinking perspectives and strategies include an emphasis on how new knowledge is acquired (Mont et al., 2021), managed, exchanged, interpreted, assimilated, and disseminated; a network-centric approach based on developing relationships among and between organizations and individuals; the theoretical basis and projections; and the use of a variety of analytic approaches (Maude et al., 2021). These perspectives and approaches are constructive in the current situation. The value relies on systems thinking-based tools and approaches for implementing transformative changes in the health system (Roy et al., 2020), when those modifications are intended to address the overhead of such systems, which include health practice, education, and policy (Li et al., 2020).

A crucial psychological component similar to cognition, to comprehend how individuals reacted to superior, medically wonderful procedures, and cutting-edge methods used during the Covid-19 epidemic (Teixeira et al., 2020).Thinking strategies involve considering how one's own and other people's activities affect one's own and other people's results. It is a common and varied mental activity (Sturmberg et al., 2020). Situations requiring strategic thinking typically have several, alternate courses of action and outcomes. As a result, decision-makers may pay diverse amounts of attention to various individuals, alternative courses of action, and various levels of potential consequences (Yang & Kim, 2022). Based on the notion that people who make decisions mostly pay attention to some parts of social circumstances more than others (Steptoe-Warren et al., 2011). The Covid-19 crisis prompted organizations to form task groups to deal with the situations as they emerged and others to think about how to resolve the crisis. According to Maude et al. (2021), there are five fundamental principles that must be followed when developing strategies to address the Covid-19 crisis in the healthcare industry: experts in the field must participate in sectoral policy development; teamwork between healthcare sectors must become the norm; solutions must take into account all sizes of the issue; federal policy management must be proactive; and the regulatory process for health systems must be rearranged.

Remarkably, healthcare organizations are committed to enhancing services, mostly by combining operational, improvement, and programme management capabilities, while taking several courses of action and potential outcomes into consideration (Spicer, 2020). The egocentric strategic perspective emphasizes how one's activities influence their results. The effect of strategic orientation emphasizes how one's activities influence the results of others (Teixeira et al., 2020). The dependence strategic perspective emphasizes how the activities of others shape one's outcomes. Last but not least, the altercentric strategic perspective emphasizes how individuals' results are shaped by the activities of others (Shreffler et al., 2020). The ability of both areas and teams to meet the predetermined goals was taken into account while computing both the area and medical team results (Saqlain et al., 2020). This method has enabled a better integration of production and performance data, which is now contained within a single matrix and, as a result, more sensitive and capable of describing the group's positioning and capability, both horizontally (in a given time, between different hospitals) (Parikh et al., 2020) and vertically (in a given hospital, across different moments) (Mont et al., 2021).

Companies were forced to rethink their business strategies (Bratianu & Bejinaru, 2020). The Information Intensity Matrix, which has been enhanced by the addition of the third dimension (affect the biodiversity of the product or service), may help explain how the pandemic has affected various business models in different industries (Graf-Vlachy et al., 2020), with a focus on the significance of agility and being ready to respond to unforeseen changes in the environment (Elhadi et al., 2021). Including the third dimension makes it possible to comprehend, for example, the stark contrast between Covid-19 effect on the banking business and the hotel industry (Roy et al., 2020). All organizations, including governments and corporations, found that they lacked the strategic expertise necessary to address this situation since the disruption created by Covid-19 was unanticipated (AL-Rawajfah et al., 2021). The only option was to change from the planned techniques employed in "normal times" to an emergent knowledge strategy, which had to form at the moment (Bhagavathula et al., 2020a).

The managers of firms are responsible for carrying out this challenging duty (or business owners in the case of small businesses) (Elhadi et al., 2021). Effective communication, teamwork, problem-solving abilities, managerial aptitudes, and decisiveness are necessary for strategic thinking to be successful (Mbachu et al., 2020). By enabling businesses to function creatively and differently from others or differently under comparable business models, strategy can help businesses gain a sustained competitive edge (Porter, 1987). During a pandemic, a strategic plan helps an organization become inventive by modifying or creating new business models to increase profitability while still servicing the target market (Roy et al., 2020). Because of this, the healthcare organizations have formed plans and implemented management initiatives to deal with the disturbance wave that Covid-19 has caused and utilize technical solutions to handle the knowledge in order to endure and be sustainable (Schiuma et al., 2021).

CHAPTER 3

METHODOLOGY

3.1 Overview and Purpose of the Study

This section will provide an in-depth analysis of the methodology utilized in the study. The subsequent subsections will cover the overview, hypotheses, constructs, population, sample, data analysis, survey design, ethical considerations, pilot study, as well as summary. By examining these sections, readers will gain a thorough comprehension of the methodology employed and the measures taken to ensure precision and dependability in the research. The purpose of this research was to investigate whether risk perception acts as a mediator between Covid-19 knowledge and strategic thinking within healthcare organizations. This information would be beneficial to public health researchers, policymakers, and healthcare business owners.

3.2 Hypotheses

The potential impact of Covid-19 knowledge and risk perception on the strategic decision-making processes of healthcare industry leaders is a topic of interest. Specifically, if the perception of risk acts as a mediator in the relationship between Covid-19 knowledge and strategic thinking, it may have significant implications for the development of effective strategies. This study's literature suggests that risk perception played a mediating role in investigating the link between Covid-19 knowledge (an independent variable) and strategic thinking (a dependent variable). As a result, this study aimed to test the following hypotheses:

H1: *Covid 19 Knowledge is positively related to Strategic Thinking*

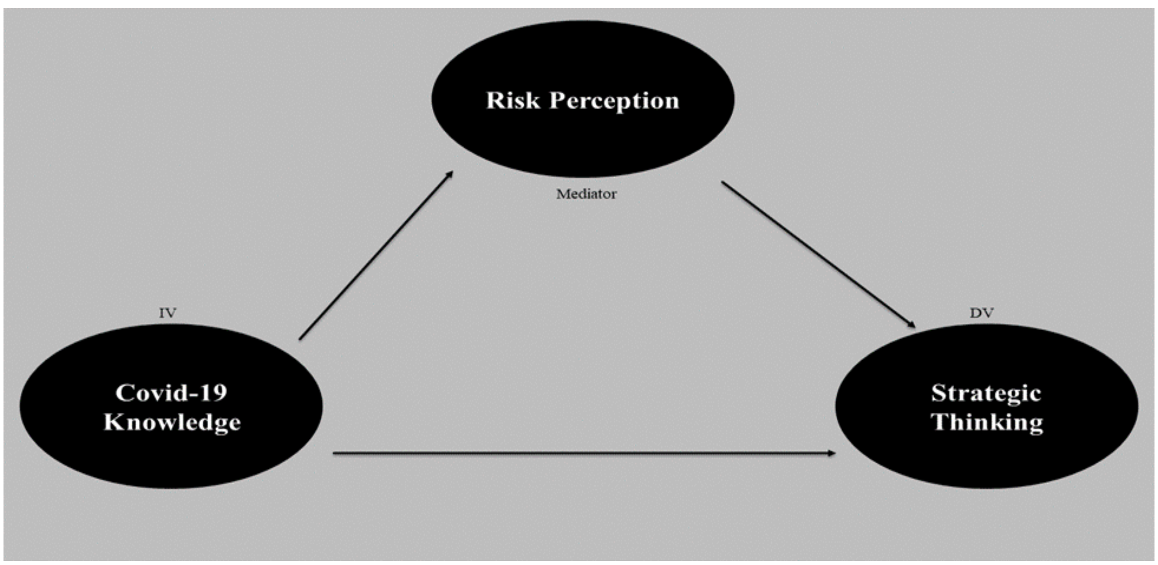
H2: *Covid-19 Knowledge is positively related to Risk Perception*

H3: *Risk Perception is related to Strategic Thinking*

H4: *Risk perception mediates the relationship between Covid-19 Knowledge and Strategic Thinking*

Figure 3.1

Showing the Proposed Conceptual Framework of the Study



3.3 Constructs

The aim of this research is to use a quantitative approach to investigate how risk perception, strategic thinking, and Covid-19 knowledge are related in healthcare organizations. The study will use mid-level managers to executives working in healthcare as respondents. The main objective of this quantitative study is to determine the extent to which risk perception intervene the relationship between strategic thinking and Covid-19 knowledge within the context of healthcare organizations.

3.3.1 Covid-19 Knowledge

The first construct will evaluate Covid-19 knowledge using a cross-sectional approach that measures using a 7-point Likert scale following the methodology of Patidar et al. (2020). In order to obtain a more precise response from participants, the methodology of Patidar et al. (2020) adopted a 7-point Likert scale response, as recommended by Vagias (2006). This approach allows for a wider range of degrees of opinion and enhances the accuracy of the responses received. The measurement of Covid-19 knowledge (CV-19K) is an important tool in assessing the level of understanding individuals have regarding the contagious disease.

The scale developed by Patidar et al. (2020) provides a suitable framework for measuring CV-19K. This scale consists of three sub-factors, namely knowledge, attitudes, and practices. However, this study focuses on the knowledge part of the scale (9-items). The knowledge subscale of the CV-19K scale comprises several questions that aim to assess the level of knowledge individuals possess regarding Covid-19. One example of a question from this scale is, "To what extent is Covid-19 a contagious disease." The responses to these questions were modified from a "Yes and No" response to a 7-Likert style response ranging from 1 (strongly disagree) to 7 (strongly agree).

The factor loading for the knowledge subscale of the CV-19K scale ranged between 0.651 to 0.781, indicating a strong correlation between the items in the scale.

The Cronbach alpha of 0.75 demonstrates acceptable reliability of the scale. Additionally, the p value of less than 0.001 indicates the significance of the results obtained in this study. In conclusion, the KAP scale developed by Patidar et al. (2020) provides a reliable and valid means of measuring Covid-19 knowledge. The knowledge subscale of this scale shows strong internal consistency and reliability, making it a useful tool in assessing individuals' understanding of Covid-19.

3.3.2 Risk Perception

To evaluate the second construct, a 7-item Likert-type scale from Erchick et al. (2022) will be used. Additionally, the risk perception (RP) of participants was assessed using a 12-item scale called the risk perception scale (RPS), which was developed by Erchick et al. (2022). The RPS was designed to assess how safe or unsafe individuals perceive the likelihood of contracting or transmitting Covid-19. For instance, participants were asked to rate their perceived safety when attending a gathering of more than 100 people and dining outdoors at crowded. Responses were measured on a Likert scale ranging from 1 (extremely safe) to 7 (Somewhat Unsafe). The current study shows high internal consistency with a Cronbach alpha of 0.99 and factor loadings of 0.65, indicating precise measurement of intended factors.

3.3.3 Strategic Thinking

The dependent construct, strategic thinking, will be assessed using a 7-item Likert-type scale adapted from Pisapia et al. (2011). According to Pisapia et al. (2011), the term strategic thinking (ST) refers to an organizational concept that centers around the identification and establishment of purpose, priorities, strategies, and tactics. The notion of strategic thinking has been extensively explored by scholars from diverse domains, including leader effectiveness, employee engagement, and organizational productivity, as highlighted by Pisapia et al. (2005). In order to evaluate ST, Pisapia et al. (2011) developed a 15-item questionnaire that comprises a range of queries, including the following sample question. “I look for fundamental long-term corrective measures, I ignore my past experiences when trying to understand situations presented to me, I reconstruct an experience in my mind” to a response to a 7-Likert style response ranging from 1(Strongly Disagree) to 7 (Strongly Agree).

The questionnaire used in this study consists of 15 items that are divided into three subscales: system thinking, reframing, and reflection. The system thinking subscale includes five items, while the reframing and reflection subscales consist of five items each. The factors loading for these subscales range from 0.60 to 0.72, indicating a strong relationship between the items and their respective subscales (Pisapia et al., 2011). To assess the reliability of the questionnaire, Cronbach’s alpha coefficient was used and yielded a score of 0.70. This score is considered sufficient by psychometric authorities such as Nunnally (1978) and Peterson (1994). The high reliability of the questionnaire suggests that it is a valid and consistent tool for measuring the constructs of system thinking, reframing, and reflection.

3.3.4 Demographics

In a study on Covid-19 knowledge and strategic thinking, Iorfa et al. (2020) found that demographic factors such as gender did not affect the relationship between Covid-19 knowledge and risk perception, while age was found to predict increased precautionary behavior as a result of strategic thinking. To make effective strategic decisions, decision-makers should consider their experience and education, recognizing the importance of practical knowledge and theoretical concepts in a comprehensive approach for optimal outcomes.

Table 3.1

Summary of Survey Questionnaire Instrument

Authors & Year	Instrument Name	No of Items	Answer Choice	Reliabilities
Patidar et al. (2020)	Covid-19 Knowledge	9	7-point Likert-type scale	α = .75
Erchick et al. (2022)	Risk Perception Questionnaire	12	7-point Likert-type scale	α = .99 (Wolf et al., 2013)
Pisapia et al. (2011)	Strategic Thinking Questionnaire	15	7-point Likert-type scale	α = .70
Miller and Simmering (2022)	CMV Color Blue	7	7-point Likert-type scale	α = .92

Note. All reliabilities shown are those reported by the original authors. α = coefficient alpha.

3.4 Population & Sample

3.4.1 Population

The present study aims to focus on a specific population for the purpose of conducting a comprehensive survey. Specifically, the target demographic will consist of individuals holding positions ranging from mid-level managers to executive employees in the healthcare sector, encompassing both full-time and part-time professionals. Furthermore, the geographical scope of the study will be limited to participants located within the United States. Statistical data provided by the Bureau of Labor Statistics (2023) estimates the presence of approximately 476,750 individuals employed as mid-level managers to executives within the healthcare industry in the United States. Thus, this research endeavors to gather responses exclusively from this particular group of healthcare professionals occupying mid-level to executive positions across the nation.

3.4.2 Sample Identification

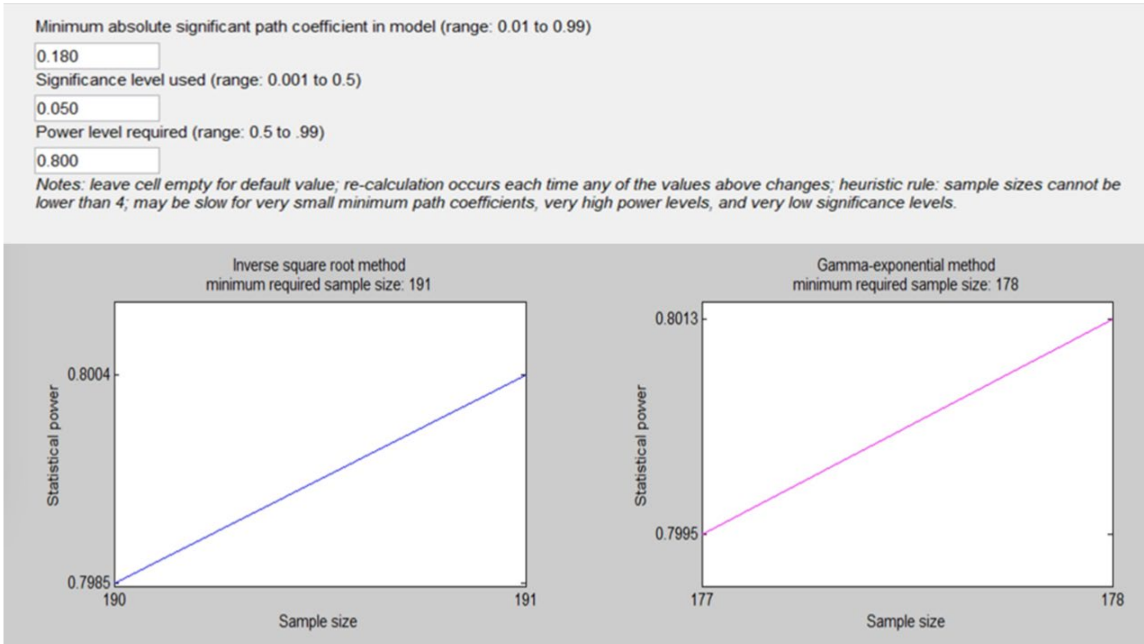
Social platforms such as Facebook and LinkedIn serve as valuable platforms for generating positive responses, with Facebook enabling rapid participant recruitment through simple postings and LinkedIn requiring more time and effort to establish connections but yielding a more diverse sample (Stokes et al., 2017). The participants for the survey were recruited through a platform that connects researchers with respondents and other online platforms such as LinkedIn and other social media platforms (Gelinas et al., 2017). Social science researchers typically use online platforms to gather participants for observational and experimental studies because of its capacity to survey large and diverse samples frequently. Social media was observed and found to be the most effective recruitment method in 12 out of 30 studies, particularly for hard-to-reach populations and observational studies, according to Topolovec-Vranic and Natarajan (2016).

3.4.3 Sample Size

As shown in Figure 2 below, the minimum absolute significant path coefficient is 0.32. Based on this, we used significance level (0.05) and power level (0.80) to estimate the minimum required sample size using both the inverse square root method and the gamma-exponential method (Ezeugwa et al., 2022). Figure 4 shows the inverse square root method generated a larger minimum required sample size (191) than the gamma-exponential method (178). In this case, the preferred minimum sample size is 178. Note that this power level is 0.800; usually the value of 0.80 is acceptable (Kock & Hadaya, 2018).

Figure 3.2

Sample Size Estimation when Power is 0.800



In order to determine the necessary sample size for the marker variable, we followed the guidelines set out by Wolf et al. (2013). The marker variable consisted of 7 items and a total of 60 participants were included. Consequently, the study intends to recruit around 278 to 300 participants using online platforms such as LinkedIn and other social platforms (Gelinas et al., 2017). Schumacker and Lomax (2016) suggest a minimum ratio of 10:1, which translates to a sample size of at least 420. (3 paths). A minimum sample size of 200 participants was required (Harris & Schaubroeck, 1990), and the cumulative sample size reached 270 based on Wolf et al.'s (2013) guidelines.

This study employed convenience sampling as a non-probability sampling technique to obtain data. Convenience sampling involves the selection of participants based on their accessibility to the researcher. Accessibility may be determined by factors such as geographical proximity, availability, or willingness to participate. Non-random selection is a characteristic of convenience sampling, also referred to as unintentional sampling. The sample population consisted of decision-making employees affiliated with healthcare organizations.

3.4.4 Data Collection Method

The data for the study will be obtained through a quantitative cross-sectional methodology, and the survey instrument utilized in the research was developed with the aid of Qualtrics®, an online survey platform that enables survey creation and storage, as well as the collection and management of responses. The decision to utilize Qualtrics®, was based on various factors, including its popularity, low cost of recruitment, high level of online literacy, potential for result transportation, and diverse participation pool, as outlined by Aguinis et al. (2021). Respondents were recruited through social media platforms (Gelinas et al., 2017), an anonymous platform with no supervision. It is crucial to consider the possibility of a nonresponse bias when conducting surveys, as it can greatly affect the accuracy of the results (Groves, 2006). Next outliers in the data were addressed. These are scores that deviate greatly from the rest of the (Field, 2018). I utilized the vertical boxplot data function available on SPSS to identify these outliers (Field, 2018). After successfully cleaning the survey data, I will move forward to evaluating the measurement of constructs. To mitigate non-response bias, measures were taken to streamline the survey process. This involved simplifying the questionnaire, providing an opt-out option, maintaining confidentiality, keeping the survey brief, and incorporating incentives to encourage participation.

3.5 Survey Design

The research instrument utilized in this study was a survey consisting of 43 items, as presented in Appendix B. The participants were provided with a set of options, out of which they had to select one answer. Before taking the survey, participants needed to answer four screening questions to ensure that they met survey requirements. The first screening question was aimed at detecting bots and preventing them from participating in the survey (Rouse, 2015). To prevent any missing data issues, all questions were mandatory (Wolf et al., 2013). As per the survey design section provided below, Qualtrics® stands as the favored methodology for its ease of configuring the survey flow and details, thereby simplifying the entire survey collection process.

To ensure the accuracy of the survey results, the questions were organized into different blocks based on the recommendations by Podsakoff et al. (2003). Each block focused on a specific variable such as the dependent variable, mediator variable, independent variable, or demographics. The order of the blocks was carefully selected to avoid any priming effects, with the dependent variable block being placed before the independent variable block. While it is recommended to randomize or counterbalance the scales within each block, it is important not to mix items from different scales indiscriminately as it may negatively impact the quality of data. As a result, subsequent blocks were not randomized.

Participants who passed the BOT and screening questions were then directed to the first set of questions which focused on the CMV and dependent variable (STS). To guarantee participants' attentiveness to the survey questions, an initial IMC was conducted. If participants were unable to pass the first IMC, they were informed of their failure but still given the option to proceed with the survey. This early IMC stage guarantees that participants will focus on their responses to subsequent inquiries. The survey progressed with inquiries about mediation (RPS), which were then followed by the independent variable (CV-19K S). Demographic questions were presented at the end of the survey, as recommended by Bourque and Field (2003). Placing demographic details at the start of the questionnaire can be discouraging for respondents, which is why they were placed at the end. You can refer to Table 3.2 for a clear understanding of the survey variables and flow.

Table 3.2

Survey Instrument Flow

Flow	Instrument
1	Marker Variable (CMV)
2.	Dependent Variable (STS)
3	Instructional Manipulation Checks (IMC)
4	Mediator (RPS)
5	Independent Variable (CV-19K)
6	Demographics

Note. IMC = instructional manipulation check, CV-19K = Covid-19 knowledge scale, STS = strategic thinking scale, RPS = risk perception scale.

3.5.1 Screening and Attention Checks

Participants will be sourced from social media platforms as stated above such as LinkedIn. As per the survey design section provided above, Qualtrics® stands as the favored methodology for its ease of configuring the survey flow and details, thereby simplifying the entire survey collection process. To be eligible for participation, individuals must meet certain prerequisites, including providing personal background information such as their geographical location, work permit status, organizational sector, and job title. Specifically, the criteria utilized for this purpose were the lack of informed consent, failure to pass screening questions, such as non-US based participants, and absence of a full-time or part-time work status in a healthcare. Furthermore, respondents who failed to pass the Bot checks were also excluded To ensure the quality of data obtained from participants, attention checks were employed to evaluate their adherence to instructions or attention to detail, as suggested by Hauser and Schwarz (2015). Afterward, the collected data will be downloaded, cleaned, and coded, and both sample characteristics and measurement characteristics will be analyzed. The conceptual framework will be evaluated by performing statistical hypothesis tests, and the resulting analysis findings will be prepared.

3.5.2 Marker Variable

To avoid the potential for common method variance (CMV) when collecting data, a marker variable was included in the study in accordance with the recommendations of Podsakoff et al. (2003). During the survey administration, participants were explicitly informed that their responses to these questions would not be evaluated as right or wrong. This approach aimed to create a non-threatening and open environment, conducive to fostering candid and genuine responses. To mitigate the potential for common method bias, all the variables of interest were collected from the same source. To further control for this bias, the survey questions were arranged and positioned in a deliberate manner (Podsakoff et al., 2003).

Lindell and Whitney (2001) proposed using the marker variable to capture CMV. Attitude toward the color blue developed by Miller and Chiodo (2008) was used. The scale used a 7-point Likert type measurement of 1(strongly disagree), to 7 (strongly agree). Miller and Simmering (2022) demonstrated a Cronbach's alpha of 0.92, surpassing Kline's (2011) established threshold of |0.85| for collinearity. Table 3.1 above is a summary of the measurement scales used in this study. The table presents the authors and dates, instrument name, number of items, answer choices, and previous reliabilities.

3.6 Ethical Considerations

The ethical conduct of research involving human subjects is ensured by the Institutional Review Board (IRB). The IRB must provide approval before the study is initiated to ensure that the subjects are not exposed to any harm. This encompasses procedures for sampling, data collection, and data management to comply with privacy laws, as well as techniques for conducting surveys and interviews. The student responsible for the research is accountable for obtaining authorization to utilize human subjects in the research. In this study, participants were directed to the survey tool's consent pages, where they were presented with an informed consent form. The informed consent form explains the study's purpose, the participants' rights, the protection of their privacy, and the characteristics of the anonymous survey. Participants were required to consent before participating in the survey; otherwise, they were directed to the end of the survey. The University of Dallas approved this study through its IRB, and the approval was received on April 11, 2023.

3.7 IRB

The acquisition of the IRB approval on April 11th, 2023, represents a significant milestone that validates the research commitment to ethical standards and ensures the safeguarding of participants' rights and well-being. The official IRB approval document is attached in Appendix A. This approval demonstrates the rigorous evaluation undergone by the research protocol, ensuring compliance with ethical norms and acknowledging potential risks.

3.8 Pilot Study

A pilot study was conducted to initiate this research, with a sample of 91 participants ($n = 91$). As Perry stated in 2001, conducting pilot studies is essential as they provide a means for researchers to assess the cost, potential errors, duration, and feasibility of a larger study, as well as the ease of obtaining participants that may not have been initially anticipated during the planning phase. Validated scales from previous studies were utilized in this study to check the participants' understanding of the questions and the time it took to complete the survey. Prescreening questions were employed to exclude individuals who need to be decision-makers in the health field, as argued by Keith et al. in 2017, it increases validity since the research is specific to a particular population. Another source, Chandler et al. (2013), demonstrated that research requiring specific skills and knowledge should employ prescreening to enhance the accuracy of collected data.

Before conducting the pilot research, IRB approval was requested and obtained as discussed in the previous section. During the pilot, certain concerns were tested and addressed, including (a) identifying eligible participants for the survey, (b) assessing the effectiveness of the Covid-19 knowledge scale, which was adapted to a 7-point Likert scale, and (c) evaluating the validity, reliability, and suitability of the research instruments for the population under investigation.

3.9 Pilot Survey Results

Only 27 completed the survey out of 91 responses with Cronbach's Alpha value of COVID-19 knowledge Questionnaire (9 items) alpha value is .447 which indicated that scale reliability is low. They are not useful because the responses were 0 and 1 therefore Cronbach alpha is not a valid measure. A 7 Likert scale by Vagias (2006) was adapted to ensure a more accurate response. Cronbach's Alpha value of The Risk Perception Questionnaire (12 items), alpha value is .924 which indicated that scale is highly reliable. Cronbach's Alpha value of subscale (Perception of safe 5 items) alpha value is .804 which indicated that scale is highly reliable. Cronbach's Alpha value of subscale (Perception of unsafe 7 items) alpha value is .919 which indicated that scale is highly reliable. Cronbach's Alpha value of Strategic Thinking Questionnaire (15items), alpha value is .750 which indicated that scale is good reliable. Cronbach's Alpha value of subscale (System thinking 5 items) alpha value is .840 which indicated that scale is highly reliable. Cronbach's Alpha value of subscale (Reframing 5 items) alpha value is .914 which indicated that scale is highly reliable. Cronbach's Alpha value of subscale (Reflecting 5 items) alpha value is .552 which indicated that scale is satisfactory reliable.

Table 3.3

Alpha Reliability of Study Scales and Sub-Scales

Scales	N of Items	Cronbach's Alpha
1. Strategic Thinking Questionnaire	15	.750
System thinking	5	.848
Reframing	5	.914
Reflecting	5	.552
2. The Risk Perception Questionnaire	12	.924
3. KAP COVID-19	9	.447

Note. KAP= Knowledge Questionnaire, RP = Risk Perception, ST= Strategic Thinking.

This evaluation was critical to ensure that the study results were both accurate and meaningful. In general, the instruments utilized in the study were appropriate for the research questions and population, resulting in reliable and informative data. Additionally, data was collected on demographic information such as gender, age, race/ethnicity, tenure with the company, and managerial status.

3.10 Assessment Measurement Validation

The structural equation modeling will be utilized to test the research model in SPSS AMOS 27 statistical software. The output estimate of scales or latent variable Cronbach's alpha (Kline, 2016) will be used to assess reliability. This method will examine the correlations among latent variables, and it was found that a p-value of less than 0.05 indicates a significant correlation with a 95% confidence level. AMOS provides assessments such as Composite Reliability (CR) and Average Variance Extracted (AVE) alongside Cronbach's Alpha test to evaluate the reliability of scales and assess their convergent and discriminant validity. The equations for calculating CR and AVE were developed by Hair et al. in 1998. Standardized regressions were also reported.

In order to investigate the relationship between Covid-19 knowledge and strategic thinking, I will utilize a method suggested by Hayes (2018) to test the mediating effect of risk perception. I will utilize bootstrapping to ensure that the inference was based on an estimate of the indirect effect itself (Hayes, 2018). My research model hypothesized that Covid-19 knowledge completely influences strategic thinking through its effect on risk perception (full mediation effect of risk perception). However, I will also consider the possibility that the effect of Covid-19 knowledge on strategic thinking might be partially mediated through risk perception (partial mediation effect of risk perception). To determine the presence of full or partial mediation effects, I will conduct a mediation analysis by "estimating and conducting an inference about the indirect effect, as it quantifies the difference in Y attributable to a one-unit change in X through the effect of X on M which in turn affects Y" (Hayes, 2018, p.6).

After controlling for Path a and Path b, the coefficient of Path c for IV was reduced, indicating that risk perception either fully or partially mediates the effects of Covid-19 knowledge on strategic thinking. Alternatively, if Path c becomes statistically insignificant and is close to zero, the analysis suggests the existence of a full mediation (Alotaibi & Zhang, 2017) and indirect effect also has to be significant. Once hypotheses testing was completed, results will be analyzed, reported, and tables depicting the results were provided.

If the Mardia statistic produces a significant result and the critical ratio is higher than 5.0, this suggests a deviation from multivariate normality (Byrne, 2010). In such cases, a 2,000-case bootstrapping procedure at the 95% confidence level will be carried out (Kline, 2016). Bootstrap's indicators, as noted by Shrout & Bolger (2002), include the critical ratio and p-value. Once all construct measures have been assessed for reliability and validity, two post hoc tests will be conducted to check for any signs of method bias. Firstly, using Harman's single-factor test as per Podsakoff et al. (2003) marker variable technique will be employed, and I will test for common method variance by loading all items from the combined dataset in factor analysis with no rotation. Additionally, I will examine the average variance extracted (AVE) to ensure individual item reliability and convergent validity of constructs. If the results are satisfactory, the next stage of testing will be initiated.

The CFA technique will be employed to assess the goodness-to-fit of the confirmatory factor analysis model. To determine the model's compatibility, a variety of goodness-to-fit indicators will be used, such as the chi-square indicator with freedom degrees, CFI indicator, and RMSEA indicator. In CFA model testing, several cut-off indices are recommended to determine the model's goodness of fit. The following criteria are used to determine the measurement model's goodness of fit: (a) RMSEA $\leq .08$, (b) SRMRs $\leq .08$, (c) CFI $\geq .90$, (d) the smallest value of the Akaike information criterion (AIC), and (e) the Bayes information criterion (Hair et al., 2012; Kline, 2016). It is important to note that relative fit indices that employ a base model should be distinguished from the relative value of fit indices (Yuan, 2005).

3.11 SEM

This study will employ structural equation modeling (SEM) using SPSS AMOS version 27 to test the measurement and structural models. SEM is widely used in research to predict the dependent variable based on independent variables and has been shown to be an effective method for combining analysis of both measurement and structural models (Kim et al., 2010). SEM integrates the assessment of all variance components of each observed variable, including measurement errors, into the same model (Dinev et al., 2008). In addition, SEM techniques allow for factor analysis and hypothesis testing within the same statistical analysis, making it the preferred method for testing theoretical models using quantitative methods (Schumacker & Lomax, 2010). According to Hair et al. (2012), conducting SEM is highly recommended in strategic research as it helps in testing theoretical constructs and their relationship with observed indicators.

3.12 Chapter Summary

In this section, I have given an overview of the research methodology utilized for this study. The items covered in this section included the overview, hypotheses, constructs with scales and sample questions, population, sample size, data collection, survey design, ethical considerations, IRB, pilot study, results, assessment measurement validation, SEM, and finally, the chapter summary. Finally, chapter four will present the outcomes of the assessments and hypotheses testing, and the results will be summarized.

CHAPTER 4

RESULTS

4.1 Overview

In this chapter, the analysis conducted, and empirical results are presented to examine the hypotheses of the research using IBM SPSS AMOS software package. The chapter comprises sub-sections, beginning with an introduction. The second section provides a general assumption in structural equation modelling (SEM). The third section presents the proposed second order and first-order latent constructs along with their respective measurement items.

The fourth section discusses data screening procedures, including the handling of missing values, outlier removal, and testing the normality of data distribution. The fifth section conducts a Common Method Bias test to assess the potential impact of common method variance. The sixth section presents the results of Confirmatory Factor Analysis (CFA) used to evaluate the uni-dimensionality, reliability, and validity of the constructs. The seventh section offers descriptive results of the constructs, while the eighth section reports on structural models, including tests of hypothesized direct effects and mediation effects. Finally, the ninth section summarizes the data analysis results and research findings.

4.1.1 Data Analysis Results

The study conducted in June 2023 aimed to explore the mediating role of risk perception in the relationship between Covid-19 knowledge and strategic thinking, emphasizing the significance of effective strategies within this context (Gelinas et al., 2017). Initially, a total of 4650 participants were engaged in data collection; however, after exclusions, the final cleaned dataset consisted of 390 participants (n=390). Among the exclusions were 163 individuals who did not provide consent, 24 participants from outside the United States, 64 who failed the BOT check, 62 who did not meet the employee requirement of a work permit, and 3004 non-healthcare employees. Furthermore, 348 participants did not hold supervisory roles, while 985 did. The average survey completion time was 7.17 minutes, and approximately 595 individuals did not finish the survey. The sample size met the recommended criteria for structural equation modeling analyses, with a minimum sample size of 200 (Harris & Schaubroeck, 1990) and a cumulative sample size of 270 participants based on Wolf et al.'s (2013) guidelines (Schumacker & Lomax, 2016).

Moreover, the accepted sample comprises 38.82% (n=151) were male, 59.14% (n=231) were female, and 2.06% (n=8) preferred not to say. The largest age group was approximately between 31 to 50 years, with about 48.3% of the respondents, followed by 18 to 30 as 40.8%, and finally 51-74 as 10.9%. The African American or Black had a cumulative of 31.36%(n=122) respondents, Hispanic as 11.32%(n=45) respondents, Caucasian or White as 47.30%(n=184), Asians or pacific Islander as 3.08%(n=12), Other as 6.17%(n=24), and Native American as 0.77%(n=3) of the respondent, these sums it up.

4.2 Structural Equation Modelling (SEM)

Structural Equation Modelling (SEM) analyses consist of two primary phases: the measurement model, also known as confirmatory factor analysis (CFA), and the structural equation model. The measurement model, represented by the CFA model, serves to uncover the relationships between manifest (observed) and latent (unobserved) variables (Ho, 2006). In essence, it outlines how latent variables are evaluated based on the manifest variables.

To assess the constructs individually, CFA was conducted for each of them, in alignment with the approach suggested by Hair et al. (2006). Subsequently, the study established a measurement model to provide specific details and evaluate it using Goodness-Of-Fit (GOF) indices, thereby establishing evidence of construct validity. For the estimation technique, Maximum Likelihood Estimation (MLE) was employed, which is a widely accepted method enabling the examination of direct effects and the correlation of error terms (Ho, 2006).

4.2.1 Convergent Validity

Structural Equation Modelling offers a notable advantage in assessing the construct validity of measurements (Hair et al., 2006). This refers to the accuracy of measurements. In the context of SEM analysis, two key components evaluate construct validity: convergence validity and discriminant validity. Convergence validity pertains to the similarity in variance degree among indicators of a specific construct. This is gauged using factor loading (standardized regression weights), Average Variance Extracted (AVE), and composite reliability (CR) across item sets within the construct. Adequate convergence is indicated by factor loading estimates ≥ 0.5 and extracted average variance ≥ 0.5 (Hair et al., 2006). Average variance extracted is calculated by dividing the sum of squared standardized factor loadings by the number of factor loadings. To demonstrate satisfactory internal consistency, composite reliability (CR) should be ≥ 0.6 (Bagozzi & Yi, 1988). Composite reliability (CR) is determined by adding the squares of factor loadings and error variance components for a specific construct (Hair et al., 2006, p. 777).

4.2.2 Discriminant Validity

Discriminant validity, as defined in the literature, pertains to the degree of distinction between different constructs (Fornell & Larcker, 1981; Hair et al., 2006). This validity can be gauged through a comparison of the square root of the Average Variance Extracted (AVE) for two constructs with their respective correlations. Evidence supporting discriminant validity is present when the correlation between the two constructs is less than the square root of the AVE for each construct. Additionally, it is advised that correlations between factors should not surpass a threshold of 0.85 (Kline, 2010).

4.2.3 Internal Reliability

To assess the reliability of measurement items for individual variables, it is crucial to conduct internal reliability analysis (Nunnally & Bernstein, 1994). Reliability in this context pertains to the extent to which a measurement is free from errors. One commonly used method to ascertain the reliability of measurement items is Cronbach's alpha coefficient, which measures internal consistency (Nunnally & Bernstein, 1994). The Cronbach's alpha coefficient ranges from 0 to 1, with higher values indicating greater reliability. To ensure a reliable scale, it is recommended that Cronbach's alpha should not fall below 0.7 (Nunnally & Bernstein, 1994).

4.2.4 Coefficient of Determinations (R^2)

The coefficient of determination, commonly referred to as R square (R^2), holds significant importance in assessing the structural model in AMOS-SEM (Hair et al., 2017). R^2 quantifies the proportion of variability in the endogenous variable(s) that can be accounted for by one or more exogenous variables. The primary criteria for evaluating the structural model encompass R^2 measures the path coefficients' level and significance. To validate the structural model's accuracy, the R-squared (R^2) value, representing the fraction of variance in the dependent variable explained by its predictors, should ideally exceed 0.30, as recommended by Cohen (1992). Chin (1998) suggests categorizations for R^2 values: above 0.67 is considered high, 0.33 to 0.67 is moderate, 0.19 to 0.33 is weak, and any R^2 below 0.19 is deemed unacceptable. Hence, the quality of the structural model hinges on the R^2 values, which signify the exogenous variable(s)' capacity to explicate the endogenous variables

4.2.5 Normality

The primary assumption when employing Maximum Likelihood Estimation (MLE) is that the data follows a normal distribution (Schumacker & Lomax, 2010). Specifically, data can be reasonably considered normally distributed if skew and kurtosis fall within the ranges of -1 to +1, -2 to +2, or even -3 to +3 (Schumacker & Lomax, 2010). Additionally, Byrne (2013) proposed a kurtosis cutoff point of less than 7 as an acceptable indicator of normality, further emphasizing that data within the range of -3 to +3 in terms of skewness can be deemed normally distributed.

4.2.6 Goodness-of-Fit (GOF)

SEM is a powerful tool in research, known for its ability to evaluate overall model fit and assess the construct validity of a proposed measurement theory, in addition to checking reliability (Hair et al., 2006; Ho, 2006). Goodness-of-Fit (GOF) indices are utilized to gauge the congruence between the proposed model's covariance matrix and the sample covariance matrix (Kline, 2010). These indices fall into three categories: absolute fit measures, incremental fit measures, and parsimonious fit measures.

Absolute fit measures include the Chi-square statistic, Goodness-of-Fit index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root-Mean-Square Residual (SRMR). The Chi-square statistic is significant when the sample size increases (Schumacker & Lomax, 2010). However, a significant p-value does not necessarily render the model unacceptable; alternative GOF indices can be considered. GFI ranges from 0 (poor fit) to 1 (perfect fit), with values over 0.90 indicating good fit (Ho, 2006). RMSEA, another absolute fit index, should be lower than 0.1 for a good fit, but values between 0.03 and 0.08 indicate an even better fit (Hair et al., 2006; Ho, 2006). SRMR is the root mean square discrepancy between observed and model-implied correlations and is considered effective when the model is not complex and the sample is under 250; a value below 0.08 is generally deemed good fit (Hair et al., 2016), although higher thresholds may be acceptable in certain cases (Kline, 2015).

Incremental fit indices, including TLI, NFI, IFI, and CFI, range from 0 (poor fit) to 1 (perfect fit), with values at or above 0.90 indicating a good fit (Bagozzi & Yi, 1988; Byrne, 2013; Hair et al., 2006; Ho, 2006). Akaike Information Criterion (AIC) and Parsimonious Normed Fit Index (PNFI) are used for model comparison, where lower AIC values and higher PNFI values indicate better fit and parsimony (Ho, 2006). To ensure adequate evidence of model fit, Hair et al. (2006) recommend using three to four fit indices, ideally including one from each of the categories: An incremental index, an absolute fit measure, and the Chi-square value with associated degrees of freedom. In this study, the following fit indices were employed: Chi-square statistic, Relative Chi-square ($\chi2/df$), GFI, AGFI, and RMSEA as absolute fit measures, along with TLI, IFI, and CFI as incremental fit indices to assess the model fit (Hair et al., 2006; Ho, 2006).

4.2.7 Common Method Bias (CMB)

Common method bias (CMB), described as the variance attributed to the measurement method rather than the constructs being measured (Podsakoff et al., 2003), can pose a significant concern in research. It manifests as a dataset bias due to external factors influencing responses, particularly when data is collected through a single method, such as manual questionnaire surveys, introducing systematic response bias (Podsakoff et al., 2003). The study at hand employed two methods to mitigate this bias: Harman's single-factor test and the CFA Marker Test. Furthermore, when utilizing self-reported survey data, researchers must be vigilant in addressing common method bias to ensure that statistical results are not confounded by respondents' social desirability, leniency, acquiescence, and other social, psychological, and measurement factors (Podsakoff et al., 2003).

4.2.7.1 Harman’s Single-Factor Test

Harman's single-factor test was utilized to assess the presence of common method variance (CMV) by subjecting all items from the combined dataset to a factor analysis without rotation. The test compares the fit of Harman's single-factor model to a confirmatory factor analysis (CFA) model. If Harman's single-factor model does not demonstrate a significantly better fit than the CFA model, it suggests that CMV is not a substantial concern (Hoyle, 1995; Podsakoff et al., 2003).

4.2.7.2 CFA Marker Test

A CFA marker test was conducted to assess model-data fit (Kline, 2016; Schumacker & Lomax, 2016). Common method bias (CMB) can threaten a study if independent and dependent variables are from the same source and context (Podsakoff et al., 2003). The test aims to detect "equality of method effects" related to the latent marker variable (Williams et al., 2010, p. 494).

To address CMB, a marker variable should be theoretically unrelated to other questionnaire scales (Lindell & Whitney, 2001). Markers serve as proxies for CMB (Simmering et al., 2015). The marker's correlation with unrelated variables estimates CMB (Lindell & Whitney, 2001). Ideal markers should be chosen a priori, theoretically unrelated, but similar in content and format to substantive variables (Richardson et al., 2009).

The CFA marker technique comprises five steps: CFA, Baseline, Model-C, Model-U, and Model-R (Williams et al., 2010). In the Baseline model, marker variables correlate with substantive factors at zero (Williams et al., 2010).

Method-C tests CMV presence by adding a direct path from the latent variable to substantive indicators (Williams et al., 2010). Factor loadings between the marker and indicators are constrained (Williams et al., 2010). If Model-C fits better than Baseline, CMV exists.

Method-U assesses whether CMV affects all substantive variables equally. Model-U retains paths from Model-C but frees factor loading estimation (Williams et al., 2010). If Model-U fits better than Model-C, CMV affects variables differently.

Model-R retains paths from Model-C/U and constrains factor correlations to Baseline values (Williams et al., 2010). Model-R should not significantly differ from Model-C/U; otherwise, CMV biases relationships (Shuck et al., 2014; Williams et al., 2010).

Reported fit statistics include χ^2, degrees of freedom, and CFI $\geq .95$ (Williams et al., 2010). Model comparisons rely on $\Delta\chi^2$ at $p \leq .05$ (Williams et al., 2010). Significant $\Delta\chi^2$ indicates method effects (Williams et al., 2010). Method-C fits better than Baseline implies no shared CMV. If Method-U doesn't fit better than Method-C, CMV affects all equally. If Method-R significantly differs from Method-C/U, CMV skews relationships (Shuck et al., 2014; Williams et al., 2010).

4.3 Construct Measures

The principal constructs in this study were evaluated using established measurement instruments. Table 4.1 provides a summary of the measurement items for the research variables, including both the first-order and second-order constructs.

Table 4.1

List of Constructs and Measurement Items

2nd Order Construct	1st Order Construct	Items Number (36)	Role	Measurement Scale
Strategic Thinking	Covid-19 Knowledge	9	IV	7-Point Likert Scale a
	Risk Perception	12	MEV	7-Point Likert Scale b
	CMV Color Blue	7	MAV	7-Point Likert Scale a
	System Thinking	5	DV	7-Point Likert Scale a
	Reframing	5	DV	7-Point Likert Scale a
	Reflecting	5	DV	7-Point Likert Scale a

Note. [a]: 1 = Strongly Disagree, 7 = Strongly Agree; [b]: 1 = Extremely Safe, 7 = Extremely Unsafe; IV = independent variable; DV = dependent variable; MEV = mediating variable; MAV = marker variable.

4.4 Data Screening

Data screening is an essential step to verify the accuracy of data entry, identify and rectify missing values and outliers, and validate the normal distribution of variables. For a comprehensive list of exogenous and endogenous variables along with their respective estimation errors in the study, please refer to Appendix C.

4.4.1 Replacing Missing Values

Missing data in a survey, defined as unanswered items by respondents, is a common concern in research. According to Cohen and Cohen (1983), when missing data amounts to 10% or less, it typically does not significantly impact the interpretation of research findings. In the context of the current study, the data screening process has revealed that there is no missing data present (Cohen & Cohen, 1983).

4.4.2 Removing Outliers

The handling of outliers is a crucial component of the data screening process. Outliers are defined as observations with distinctive characteristics that set them apart from the rest (Hair et al., 1998). Detection of outliers involves both univariate methods, such as histograms, box plots, and standard z-scores, as well as multivariate techniques like the Mahalanobis D2 distance. It is essential to identify outliers as they have the potential to disrupt data normality and subsequently impact statistical outcomes (Hair et al., 1998; Tabachnick & Fidell, 2001).

4.4.2.1 Univariate Outliers

In univariate detection, various methods were employed to assess the distribution of variables. These methods included the examination of histograms and box-plots, as well as the calculation of standardized (z) scores. According to Hair (1998), in the case of a large sample size exceeding 200, a standardized (z) > 4 indicates the presence of an extreme observation. A summary of the standardized (z) scores for the individual items within each construct is provided in Table 4.2 (Hair, 1998).

Table 4.2

Result of Univariate Outlier Based on Standardized Values

1st Order Construct	Item	Standardized value (Z-Score)	
		Min Value	Max Value
Covid-19 Knowledge	KCV_19_1	-2.654	.734
	KCV_19_2	-1.548	1.433
	KCV_19_3	-1.693	1.520
	KCV_19_4	-2.655	1.006
	KCV_19_5	-1.185	1.952
	KCV_19_6	-2.406	1.097
	KCV_19_7	-2.726	.880
	KCV_19_8	-2.445	.977
	KCV_19_9	-2.834	.802
Risk Perception	RPS1	-1.342	2.198
	RPS2	-1.366	1.950
	RPS3	-1.531	1.345
	RPS4	-1.184	2.736
	RPS5	-1.282	1.788
	RPS6	-1.441	1.827
	RPS7	-1.331	1.800
	RPS8	-1.588	1.561
	RPS9	-1.221	2.289
	RPS10	-1.120	2.228
	RPS11	-1.382	1.701
	RPS12	-1.495	1.766
System Thinking	SYT1	-2.510	1.118
	SYT2	-2.602	.997
	SYT3	-2.497	1.012
	SYT4	-2.805	.965
	SYT5	-3.097	.896
Reframing	RFM1	-1.393	1.668
	RFM2	-1.362	1.741
	RFM3	-1.373	1.795
	RFM4	-1.650	1.466
	RFM5	-1.655	1.471

1st Order Construct	Item	Standardized value (Z-Score)	
		Min Value	Max Value
Reflecting	RFT1	-2.583	1.162
	RFT2	-2.910	1.192
	RFT3	-2.450	1.107
	RFT4	-2.819	.992
	RFT5	-2.729	1.067

The research findings, presented in Table 4.2, reveal that the standardized (z) scores of the research variables fell within the range of -3.097 to 2.758. This range indicates that none of the variables exceeded the established threshold of ±4, suggesting the absence of any univariate outliers among the observations.

4.4.2.2 Multivariate Outliers

Multivariate detection was employed to analyze the data, with the Mahalanobis distance method effectively identifying multivariate outliers (Hair et al., 1998). Mahalanobis D-squared distances were computed for each case using AMOS regression, where the case number served as the dependent variable, and all non-demographic measures were treated as independent variables. A D2 / df value greater than 3.5 was considered indicative of a potential multivariate outlier. In the results (Appendix B), the largest D2 value, 114.119, belonged to case 284. However, when considering the 81 exogenous and endogenous variables, along with their relative estimation errors (Appendix A), the maximum D2 / df ratio was calculated as 1.409 (114.119 / 81), which was well below the 3.5 cutoff. Consequently, it was determined that there were no multivariate outliers among the cases, and all observations were retained for subsequent analysis.

4.4.3 Assessment of the Data Normality

4.4.3.1 Univariate Normality

The normality test was conducted as the main pre-assumption for maximum likelihood estimation to assess the normal distribution of the data of constructs. Table 4.3 presents the results of the normality test for all items and variables in the model.

Table 4.3

Assessment of Normality for Measurement Model

1^{st} Order Construct	Item	Skewness	Critical Ratio	Kurtosis	Critical Ratio
Covid-19 Knowledge	KCV_19_1	-1.376	-11.093	.838	3.380
	KCV_19_2	-.209	- 1.688	-1.142	-4.604
	KCV_19_3	-.226	- 1.823	-.999	-4.028
	KCV_19_4	-1.254	-10.112	.864	3.481
	KCV_19_5	.396	3.196	-.915	-3.687
	KCV_19_6	-.867	-6.988	-.125	-.503
	KCV_19_7	-1.183	-9.534	.570	2.298
	KCV_19_8	-.876	-7.059	-.214	-.862
	KCV_19_9	-1.274	-10.271	.760	3.063
Risk Perception	RPS1	.603	4.862	-.377	-1.521
	RPS2	.499	4.027	-.86	-3.466
	RPS3	.005	.044	-1.369	-5.520
	RPS4	1.114	8.978	.803	3.236
	RPS5	.446	3.592	-1.004	-4.049
	RPS6	.359	2.895	-.842	-3.396
	RPS7	.409	3.295	-.967	-3.897
	RPS8	.012	.100	-1.143	-4.607
	RPS9	.733	5.907	-.385	-1.553

1st Order Construct	Item	Skewness	Critical Ratio	Kurtosis	Critical Ratio
	RPS10	.882	7.114	-.21	-.846
	RPS11	.302	2.438	-1.124	-4.531
	RPS12	.155	1.251	-1.051	-4.238
System Thinking	SYT1	-.928	-7.483	.168	.678
	SYT2	-1.045	-8.423	.337	1.358
	SYT3	-.992	-7.996	.211	.849
	SYT4	-1.111	-8.959	.703	2.832
	SYT5	-1.401	-11.297	1.738	7.006
Reframing	RFM1	.187	1.504	-1.212	-4.886
	RFM2	.214	1.723	-1.141	-4.598
	RFM3	.339	2.735	-1.081	-4.360
	RFM4	131	-1.054	-1.183	-4.770
	RFM5	-.159	-1.279	-1.120	-4.515
Reflecting	RFT1	-.831	-6.700	.129	.518
	RFT2	-.948	-7.644	.712	2.870
	RFT3	-.786	-6.336	.193	-.778
	RFT4	-1.038	-8.372	.499	2.010
	RFT5	-.965	-7.778	.288	1.163

The results of the study demonstrate that all items and variables exhibited skew and kurtosis values falling within the range of ±3 to ±7. This suggests that the data set for all items conforms to a normal distribution. Specifically, the skewness ranged from -1.401 to 1.101, and the kurtosis ranged from -1.212 to 1.738 as illustrated in Table 4.3.

4.4.3.2 Mardia's Multivariate Normality

Multivariate normality was assessed using Mardia's procedures (Mardia, 1970; Mardia, 1974), as recommended by Hair et al. (2017) and Cain et al. (2017). If either the multivariate skewness or kurtosis yielded a p-value below 0.05, the data was considered non-multivariate normal (Hair et al., 2019; Ramayah et al., 2018). To perform this assessment, the software available at:

https://webpower.psychstat.org/models/kurtosis/results.php?url=95cbe4fd9bcc8d5f642ec963e53c1e6f, as suggested by Hair et al. (2017) and Ngah et al. (2020), was utilized.

The results of Mardia's multivariate normality test indicated non-normality in both multivariate skewness ($\beta = 6.015$, $p < 0.001$) and multivariate kurtosis ($\beta = 58.780$, $p < 0.001$), signifying that the collected data deviated from multivariate normality. This deviation was further confirmed by a critical ratio of 52.168, exceeding the threshold of 5.0, as noted by Byrne (2010). Consequently, a re-sample bootstrapping procedure with 2,000 samples at a 95% confidence level was conducted for the AMOS-SEM analysis, following Byrne (2010) and Kline (2016).

Bootstrap analysis, according to Shrout and Bolger (2002), involves assessing indicators such as the Critical Ratio and p-value. The results demonstrated that the non-bootstrapped estimates did not substantially differ from the bootstrapped estimates, indicating that the data could be considered multivariate normal with no outliers. The structural model reported bootstrapped standardized indirect and direct effects (Kline, 2016).

4.5 Common Method Bias (CMB)

4.5.1 Harman's Single-Factor Test

In Table 4, the outcomes of Model Fit Indices for both the Confirmatory Factor Analysis (CFA) model and Harman's single-factor model are presented. The CFA model is illustrated in Appendix C, while Harman's Single Factor model can be found in Appendix E.

Table 4.4

Model Fit Indices for CFA Model and Harman's Single Factor

Model Description	χ^2	*df*	RMSEA	GFI	CFI	SRMR	LR of $\Delta\chi2$	Model Comparison
M1: CFA	1870.965	588	.075	.769	.840	.085	$\Delta\chi^2$ = 3309.575, Δdf = 6, $p < 0.001$	vs. CFA
M2: Herman's Single Factor	5180.540	594	.141	.419	.429	.178		

Note. $\chi2$ = chi-square value, *df* =degree of freedom, RMSEA = root mean square error of approximation, GFI = Goodness-of-Fit index, CFI = comparative fit index, NFI = Normed Fit Index (NFI), CFA = confirmatory factor analysis, SRMR = standardized root mean square residuals, LR = likelihood ratio test.

In the analysis, Harman's single-factor test was conducted in Model 2, and the results, as presented in Table 4, indicated a poor fit for the data ($\chi2$ = 5180.540). In contrast, the Confirmatory Factor Analysis (CFA) conducted in Model 1 shows $\chi2$ value ($\chi2$ = 1870.965). However, the significant difference between the two models was observed, with $\Delta\chi2$ (6) = 3309.575, $p < 0.001$, suggesting that common method variance is not a significant issue in the dataset

4.5.2 CFA Marker Test

In the study, CMV Color Blue (CCB) was selected as the marker variable due to its utilization of a 7-point Likert-type scale and its theoretical independence from other variables under investigation. Table 4.5 displays the findings related to Model Fit Indices for the Confirmatory Factor Analysis (CFA) model incorporating the marker variable. The CFA model with the marker variable is presented in Appendix F, while Appendices G, H, and I respectively illustrate the Baseline, Constrained (method C), and Unconstrained models (method U). Additionally, Appendix J presents the Restricted model (method R).

Table 4.5

Model Fit Indices and Model Comparisons for CFA Model with Marker Variable

Model Description	χ^2	*df*	RMSEA	GFI	CFI	SRMR	LR of $\Delta\chi2$	Model Comparison
M1: CFA with marker variable	2382.417	851	.068	.759	.861	.077	$\Delta\chi2$ = -53.012,	vs. Baseline
M2: Baseline	2554.626	861	.071	.748	.847	.152	$\Delta df = 1$, $p < 0.001$	
M3: Constrained	2501.614	860	.070	.748	.851	.116	$\Delta\chi^2$ = -155.419,	vs. Constrained
M4: Unconstrained	2346.195	838	.068	.763	.863	.071	$\Delta df = 22$, $p < 0.001$	
M5: Restricted	2390.062	841	.069	.760	.860	.077	$\Delta\chi^2$ = 43.867 $\Delta df = 2$, $p < 0.001$	vs. Unconstrained

Note. $\chi2$ = chi-square value, df =degree of freedom, RMSEA = root mean square error of approximation, GFI = Goodness-of-Fit index, CFI = comparative fit index, NFI = Normed Fit Index (NFI), CFA = confirmatory factor analysis, SRMR = standardized root mean square residuals, LR = likelihood ratio test, AIC = Akaike information criterion, BIC = Bayes information criterion.

As shown in Table 4.5, the baseline model results were: $\chi^2 = 2554.626$, df = 861, RMSEA = 0.071, GFI = 0.748, CFI = 0.851, SRMR = 0..116. The constrained model results provided a statistically better fit to the baseline model; $\Delta\chi^2$ (1) = -53.012, $p < 0.001$, RMSEA = 0.070, GFI = 0.748, CFI = 0.851, SRMR = 0.116. This phenomenon provided the evidence of shared CMV between the indicators of the substantive variables and the latent marker variable.

The unconstrained model results provided a statistically better fit to the constrained model; $\Delta\chi^2$ (22) = -155.419, $p < 0.001$, RMSEA = 0.068, GFI = 0.763, CFI = 0.863, SRMR = 0.071. This phenomenon provided the evidence of different CMV for all indicators.

The restricted model results provided a statistically better fit to the unconstrained model; $\Delta\chi^2$ (2) = 43.867, $p < 0.001$, RMSEA = 0.069, GFI = 0.760, CFI = 0.860, SRMR = 0.077. Therefore, there is no evidence of CMV than can skew the relationships among the substantive variables.

4.6 Measurement Model (CFA)

Operationalizing constructs is a crucial step in ensuring research accuracy (Hair, 2006). Researchers face the choice of utilizing established scales to enhance theoretical precision; however, the challenge of lacking suitable scales often compels them to create new measurement scales or adapt existing ones to suit their specific context (Hair, et al., 2006). Consequently, the foundation for Structural Equation Modeling analysis hinges on selecting the appropriate items for construct measurement. This study involved a comprehensive Confirmatory Factor Analysis model, with subsequent sections elaborating on the development of the measurement model and the examination of construct unidimensionality using AMOS 29.0.

In this research, 36 items were employed to assess five first-order constructs and one second-order construct, as detailed in Table 4.1. The initial CFA model featuring all 36 items is provided in Appendix C.

4.6.1 Standardized Loadings of the Model's Items

Table 4.6 displays the items that were removed from the model, along with the reevaluated factor loadings for the retained items. The second CFA model, conducted subsequent to the removal of items with inadequate factor loadings, is presented in Appendix K.

Table 4.6

Standardized Factor Loadings in CFA Model

Construct	Item	1st Factor Loading	Deleted	2nd Factor Loading
1st Order Construct				
Covid-19 Knowledge (CV-19K)	KCV_19_1	.755		.755
	KCV_19_2	.254	Deleted	
	KCV_19_3	.313	Deleted	
	KCV_19_4	.742		.735
	KCV_19_5	.066	Deleted	
	KCV_19_6	.671		.663
	KCV_19_7	.795		.796
	KCV_19_8	.726		.730
	KCV_19_9	.847		.855
Risk Perception (RPS)	RPS1	.584		.584
	RPS2	.741		.741
	RPS3	.760		.760
	RPS4	.640		.640

Construct	Item	1st Factor Loading	Deleted	2nd Factor Loading
1st Order Construct				
	RPS5	.593		.593
	RPS6	.653		.653
	RPS7	.714		.714
	RPS8	.731		.731
	RPS9	.656		.656
	RPS10	.624		.624
	RPS11	.718		.718
	RPS12	.682		.682
System Thinking (SYT)	SYT1	.759		.759
	SYT2	.830		.830
	SYT3	.828		.828
	SYT4	.828		.828
	SYT5	.853		.854
Reframing (RFM)	RFM1	.795		
	RFM2	.859		
	RFM3	.727		
	RFM4	.581		
	RFM5	.714		
Reflecting (RFT)	RFT1	.835		.835
	RFT2	.869		.869
	RFT3	.679		.679
	RFT4	.764		.764
	RFT5	.703		.703
2nd Order Construct				
Strategic Thinking (SST)	SYT	.952		.959
	RFM	.169	Deleted	
	RFT	.856		.850

As analyzed and shown in Table 4-6, the model item loadings showed KCV_19_2, KCV_19_3, KCV_19_5, and RFM exhibited standardized factor loadings of 0.254, 0.313, 0.066, and 0.169, respectively. Since all of these values fell below the 0.5 cutoff threshold, these items were subsequently excluded from the model. Subsequent testing of the revised model confirmed the stability of its factor structure, with second standardized factor loadings for all items ranging from 0.584 to 0.959.

4.6.2 Goodness of Fit Indices

In the study, it was found that the second iteration of the measurement model did not provide adequate model fit, as indicated by a Goodness of Fit Index (GFI) of 0.846, falling below the recommended threshold of 0.9 (Hoyle, 1995). This inadequacy was attributed to high covariance discrepancies between certain item errors, with modification indices (MI) exceeding 15, indicating the presence of redundant items in the model. For instance, the MI for the covariance between the errors of SYT 1 and SYT 2 was 42.464, implying that treating this covariance as a free parameter in subsequent analyses would substantially reduce the discrepancy. These items loaded onto the same construct (System Thinking), making the within-construct error covariance a threat to construct validity (DeVellis, 2011). Similar issues were observed for other item pairs, such as RFT3&5, RFT1&2, RPS9&10, RPS5&6, and SYT1&2. To address these issues and improve model fit, it was decided to introduce correlation paths between these item errors (Hair et al., 1995).

Additionally, the model revealed covariance between error terms of indicator variables loading on different constructs, with high MI values indicating significant between-construct error covariance for items like RPS12 and RPS10. This suggested the presence of cross-loadings in the model, potentially compromising discriminant validity

(Bentler, 1980). Consequently, it was decided to eliminate RPS12 and RPS4 from the model rather than introducing correlation paths between their error terms (Awang, 2012).

Further analysis of standardized residual covariance demonstrated that all items had acceptable absolute values below the threshold of ±4 when compared to other items in the model, ranging between -3.452 and 3.356. Following the iterative introduction of correlation paths and adjustments, the modified measurement model was re-evaluated, and the results of the goodness-of-fit indices are presented in Table 4.7.

Table 4.7

GOF Indices of Modified Measurement Model

Fit index	Modified Model	Recommended values	Source
CMIN (χ^2)	553.946		
df	0288		
p-value	.000	> 0.05	
χ^2/df	1.923	≤ 5.00	Bagozzi and Yi (1988)
GFI	.902	≥ 0.90	Hoyle (1995)
AGFI	.880	≥ 0.80	Chau and Hu (2001)
CFI	.955	≥ 0.90	Bagozzi and Yi (1988); Byrne, 2013
TLI	.949	≥ 0.90	Hair et al., (2006); Ho, (2006)
IFI	.955	≥ 0.90	Hair et al., (2006); Ho, (2006)
RMSEA	.049	≤ 0.10	Schumacker and Lomax, 2010
SRMR	.055	≤ 0.08	Hu & Bentler,1999

Note. χ^2 = chi-square value, df =degree of freedom, GFI = goodness of fit, CFI = comparative fit index, RMSEA = root mean squared error of approximation, SRMR = standardized root mean square residuals.

The results of the Goodness of Fit (GOF) analysis indicated that the chi-square test was statistically significant at the $p < 0.001$ level (Hair et al., 1993). However, it was noted that when the sample size exceeded 200, the absolute fit index based on the minimum discrepancy chi-square could be disregarded. In terms of fit indices, the GFI scored 0.902, surpassing the recommended cutoff of 0.9 set by Hoyle (1995). The adjusted Goodness of Fit Index (AGFI), after adjusting for degrees of freedom relative to the number of variables, reached 0.880, exceeding the cutoff of 0.80 as suggested by Chau and Hu (2001). This value indicated that the model effectively predicted 88% of the variances and covariances within the survey data.

Furthermore, the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Incremental Fit Index (IFI) all exhibited values greater than the recommended threshold of 0.9 (0.955, 0.949, and 0.955, respectively), indicating a good fit for the model (Bagozzi and Yi, 1988; Byrne, 1998; Hair et al., 2006; Ho, 2006). Additionally, the RMSEA was 0.049, below the threshold of 0.1 as advised by Schumacker and Lomax (2010), while the SRMR was 0.055, below the threshold of 0.08 recommended by Hu and Bentler (1998). These results collectively suggest a favorable model fit. Lastly, the Relative Chi-Square (CMIN) divided by degrees of freedom (df) ratio was 1.923, which was less than the recommended value of 5, indicating a good fit for the model (Bagozzi and Yi, 1988).

4.6.3 Reliability and Convergent Validity

After establishing the unidimensionality of the constructs, the next step involved evaluating the reliability and validity of each construct. Reliability was evaluated through various measures including Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The assessment of validity encompassed the examination of construct validity, which includes both convergent and discriminant validity. The results of convergent validity and Cronbach's alpha for the modified measurement model are presented in Table 4.8.

Table 4.8

Results of Convergent Validity & Cronbach Alpha

Construct	Item	Factor Loading	AVE[a]	CR[b]	α
1st Order Construct					
Covid-19 Knowledge (CV-19K)	KCV_19_1	.756	.574	.889	.888
	KCV_19_4	.735			
	KCV_19_6	.661			
	KCV_19_7	.796			
	KCV_19_8	.731			
	KCV_19_9	.854			
Risk Perception (RPS)	RPS1	.598	.461	.894	.895
	RPS2	.746			
	RPS3	.791			
	RPS4	.635			
	RPS5	.567			
	RPS6	.646			
	RPS7	.729			
	RPS8	.736			
	RPS9	.629			
	RPS11	.677			

Construct	Item	Factor Loading	AVE[a]	CR[b]	α
1st Order Construct					
System Thinking (SYT)	SYT1	.730	.661	.907	.911
	SYT2	.833			
	SYT3	.837			
	SYT4	.804			
	SYT5	.854			
Reflecting (RFT)	RFT1	.774	.572	.869	.881
	RFT2	.815			
	RFT3	.672			
	RFT4	.802			
	RFT5	.709			
2nd Order Construct					
Strategic Thinking (SST)	SYT	.953	.813	.896	.941
	RFT	.847			

Note. α = Cronbach Alpha;

AVE = Average Variance Extracted = (summation of the square of the factor loadings)/{(summation of the square of the factor loadings) + (summation of the error variances)}.

CR = Composite reliability = (square of the summation of the factor loadings)/{(square of the summation of the factor loadings) + (square of the summation of the error variances)}.

In the study, Table 4.8 showed assessed factor loadings of various indicators, revealing high values ranging from 0.572 to 0.813, indicating the preservation of factor meaning. Additionally, the Average Variance Extracted (AVE) for most indicators exceeded the recommended threshold of 0.5, as proposed by Nunnally and Bernstein (1994), with values ranging from 0.572 to 0.813. However, the AVE for Risk Perception

(RPS) fell slightly below this threshold at 0.461. Nevertheless, it's noteworthy that when AVE is less than 0.5 but composite reliability exceeds 0.6, the construct's convergent validity remains adequate (Fornell & Larcker, 1981).

The study also reported composite reliability values above the recommended threshold of 0.6, as suggested by Bagozzi and Yi (1988), ranging from 0.869 to 0.907. Furthermore, the Cronbach's Alpha values, indicating measurement error, exceeded the threshold of 0.7 proposed by Nunnally and Bernstein (1994), ranging from 0.881 to 0.941 for all constructs. Consequently, the achieved Cronbach's Alpha values for all constructs were considered sufficiently error-free

4.6.4 Discriminant Validity

Discriminant validity, which assesses the distinctiveness of a construct from others, was evaluated in accordance with Kline's (2005) recommendation that correlations between factors in the measurement model should not exceed 0.85. The examination of validity was conducted by comparing the correlations between constructs with the square root of the average variance extracted for each construct, as proposed by Fornell and Larcker (1981). The results of the discriminant validity analysis are presented in Table 4.9.

Table 4.9

Discriminant Validity of Modified Measurement Model

	CV-19K	RPS	SST
Covid-19 Knowledge (CV-19K)	.758		
Risk Perception (RPS)	.126	.679	
Strategic Thinking (SST)	.795	-.013	.902

Note. Diagonals represent the square root of the average variance extracted while the other entries represent the correlations.

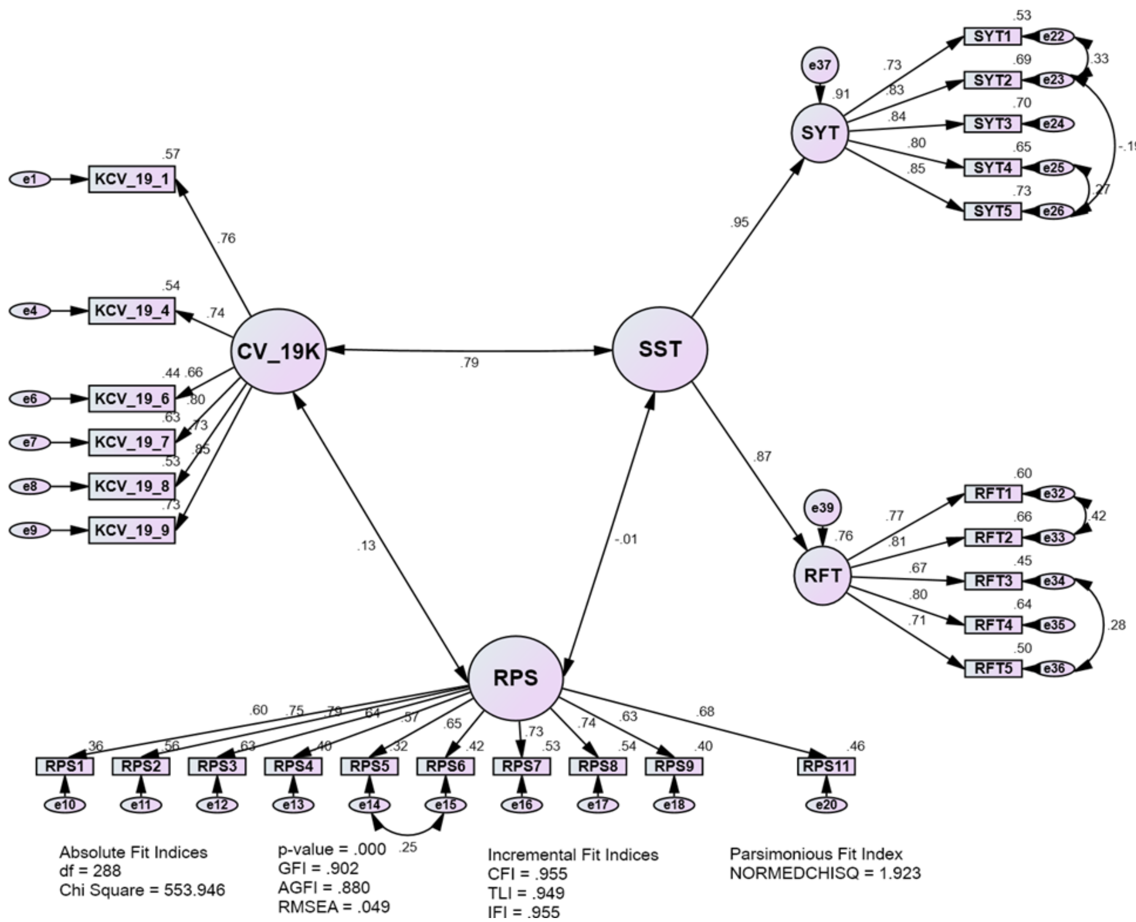
In the study, inter-correlations among the three proposed constructs were examined, revealing values ranging from -0.013 to 0.795, which all fell below the recommended threshold of 0.85 set by Kline (2005) (Table 4.9). Additionally, these correlations were lower than the square root of the average variance extracted by the indicators, except for the correlation between Covid-19 Knowledge (CV-19K) and Strategic Thinking (SST), which was slightly higher (0.795) than the square root of the average variance extracted of Covid-19 Knowledge (CV-19K) (0.758). However, as this correlation remained below 0.85 and exhibited only minimal differences from the square root of the average variance extracted, it still supports the discriminant validity of the constructs (Kline, 2005).

After scrutinizing the goodness-of-fit, convergent validity, and discriminant validity of the measurement model, it can be concluded that the modified measurement model used to assess the constructs and their respective items is both reliable and valid.

The standardized factor loadings of the items in the modified measurement model are presented in Figure 4.1.

Figure 4.1

Modified Measurement Model



4.7 Descriptive Analysis

In this analysis, the covariance matrix method was employed to compute the descriptive function, facilitating the inclusion of all variables in the analysis. Composite scores for the variables were derived by parceling the original measurement item scores, which involved aggregating several individual indicators or items according to their factor loadings on the construct (Coffman & Maccallum, 2005; Hair et al., 2006). Table 4.10 presents the means and standard deviations of the constructs, which were assessed using a 7-point Likert scale.

Table 4.10

Results of Descriptive Statistic for Variables

Constructs	Mean	Standard Deviation	Minimum	Maximum
Strategic Thinking (SST)	4.925	1.153	.81	6.47
• System Thinking (SYT)	5.055	1.233	.88	6.58
• Reflecting (RFT)	4.505	1.053	.81	5.95
Covid-19 Knowledge (CV-19K)	5.412	1.277	1.01	6.98
Risk Perception (RPS)	2.537	.961	.66	4.95

In the study, the mean was utilized as a measure of central tendency, revealing that, except for Risk Perception all other constructs had mean values above the midpoint level of 4, as displayed in Table 4.10. The phenomenon indicated that the consensus respondents' perception toward these constructs were above the average. The highest mean rating belonged to Covid-19 Knowledge with the mean value of 5.412. The lowest mean rating belonged to Risk Perception with the mean value of 2.537. The standard deviation was applied as a dispersion index to indicate the degree to which individuals within each variable differ from the variable mean. Among the studied variables, the individual value of Covid-19 Knowledge deviated the most from its mean (SD = 1.277). This standard deviation suggested reasonably high variability in respondents' perception toward Covid-19 Knowledge. In other words, the survey participants were most varying from each other in this variable. At the other side, the lowest deviation from mean belonged to Risk Perception with the standard deviation of 0.961.

4.8 Structural Models

After validating the measurement model, the connections between constructs are defined, providing insight into the relationships between independent and dependent variables (Hair et al., 2006). Assessment of the structural model begins with evaluating overall fit and then scrutinizing parameter estimates' size, direction, and significance using path diagrams (Hair et al., 2006). The study concludes by confirming the structural model based on proposed variable relationships.

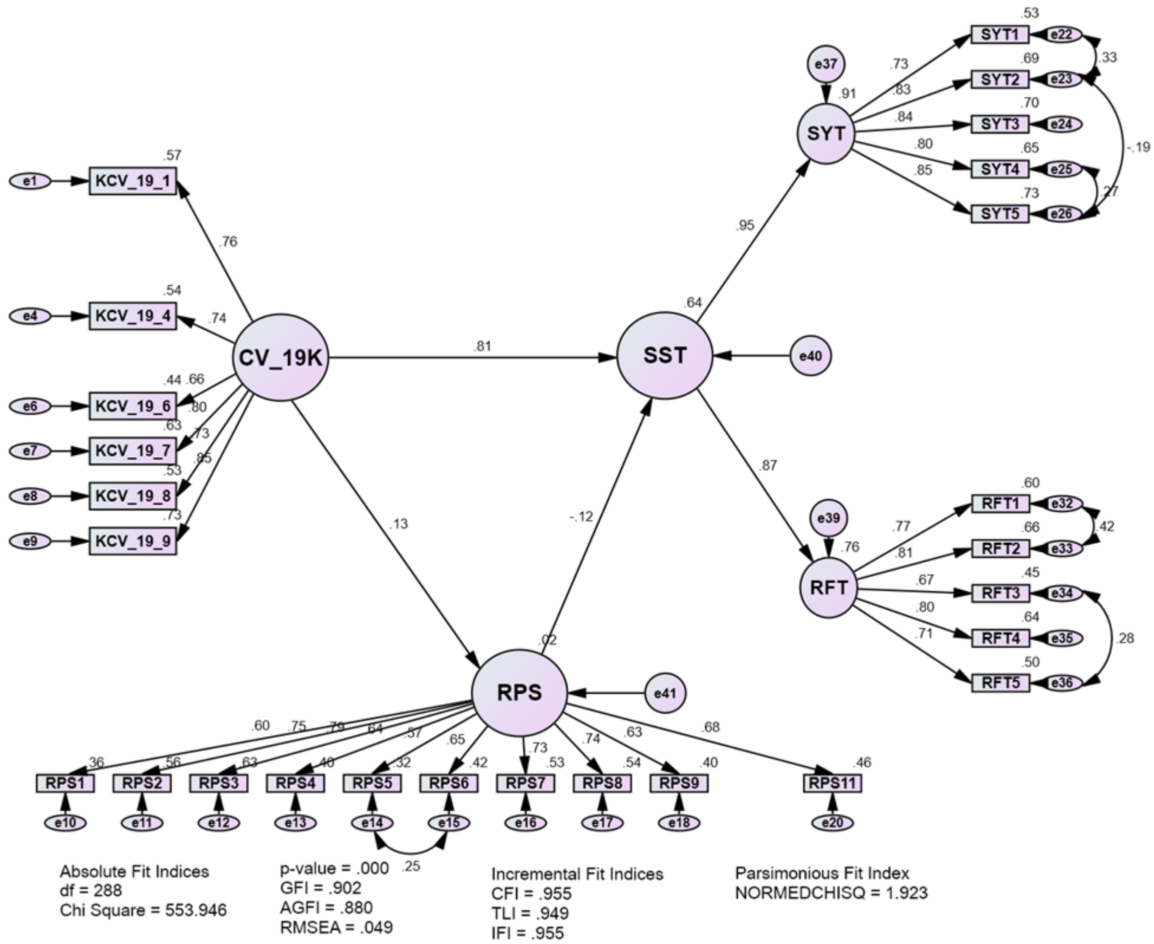
This investigation employed AMOS version 29 and the maximum likelihood estimation technique to estimate the structural model, enabling the testing of research hypotheses. Subsequent sections will elaborate on the development of the structural model for hypothesis testing.

4.8.1 Examining Direct Effects Hypotheses

In the structural model, the study investigated the direct effects of Covid-19 knowledge on strategic thinking and risk perception, as well as the direct effect of risk perception on strategic thinking (H1, H2, and H3, respectively). Figure 4.2 displays the AMOS graph illustrating the structural model, which includes the standardized regression weights for these direct effects.

Figure 4.2

AMOS Graph of Structural Model for Direct Effects between the Variables



An examination of goodness-of-fit indices indicates that the model adequately fits the data: χ^2 = 553.946, df = 288, p = 0.000, GFI = 0.902, AGFI = 0.880, CFI = 0.955, TLI = 0.949, IFI = 0.955, RMSEA = 0.049, and χ^2/df = 1.923. The chi-square statistic is statistically significant, this is not deemed unusual given the large sample size.

The strategic thinking R^2 = 0.64, indicating a relatively high magnitude of explained variance, as suggested by Chin (1998). This means that 64% of the variations in strategic thinking are explained by its two predictors, namely Covid-19 knowledge and risk perception.

The p-value of 0.028 suggests a statistically significant relationship between Covid-19 knowledge and risk perception, as it is below the conventional significance level of 0.05. However, the R^2 of 0.126 indicates that Covid-19 knowledge explains only 12.6% of the variability in risk perception. The path coefficients and the results of this examination can be found in Table 4.11.

Table 4.11

Examining Results of Hypothesized Direct Effects of the Variables

Path	Unstandardized Estimate		Standardised Estimate	critical ration (c.r.)	P-value	Hypothesis Result
	Estimate	S.E.	R^2			
CV-19K →SST	.740	.056	$.809^{***}$	13.190	.000	H1: Supported
CV-19K →RPS	.095	.043	$.126^{*}$	2.202	.028	H2: Supported
RPS→SST	-.139	.051	$-.115^{**}$	-2.713	.007	H3: Supported

Note. *p< 0.05, **p< 0.01, ***p< 0.001

In a path analysis conducted in the study, it was found that all paths between the constructs exhibited statistically significant positive direct effects, with p-values better than the established threshold of 0.05 (Table 4.11). Consequently, the hypotheses H1, H2, and H3 were supported. Furthermore, the analysis identified Covid-19 knowledge (CV-19K) as the most influential predictor of strategic thinking (SST), with a standardized path coefficient of 0.809. The subsequent section delves into a comprehensive discussion of each hypothesis.

H1: ***Covid-19 Knowledge has a significant positive effect on Strategic Thinking***

According to the findings presented in Table 4.11. Covid-19 Knowledge has a substantial and statistically significant impact on Strategic Thinking with a critical ratio (c.r.) of 13.190 ($p < 0.000$). In essence, the regression weight for Covid-19 Knowledge in predicting Strategic Thinking is significantly different from zero at the 0.001 level (two-tailed), providing support for Hypothesis 1 (H1). Furthermore, the standardized estimate of Beta was calculated as 0.809, indicating a positive relationship. This signifies that when Covid-19 Knowledge increases by 1 standard deviation, Strategic Thinking also increases by approximately 0.809 standard deviations.

H2: ***Covid-19 Knowledge has a significant positive effect on Risk Perception***

According to the results presented in Table 4.11, the critical ratio and p-value for the predictive relationship between Covid-19 Knowledge and Risk Perception were found to be 2.202 ($p = 0.028$). In simpler terms, the regression weight for Covid-19 Knowledge in the prediction of Risk Perception is statistically significant different from zero at the 0.05 level (two-tailed), thereby providing support for H2. Additionally, the standardized estimate of Beta was calculated to be 0.126, indicating a positive correlation. Specifically, when Covid-19 Knowledge increases by 1 standard deviation, Risk Perception also increases by 0.126 standard deviations.

H3: ***Risk Perception is related to Strategic Thinking***

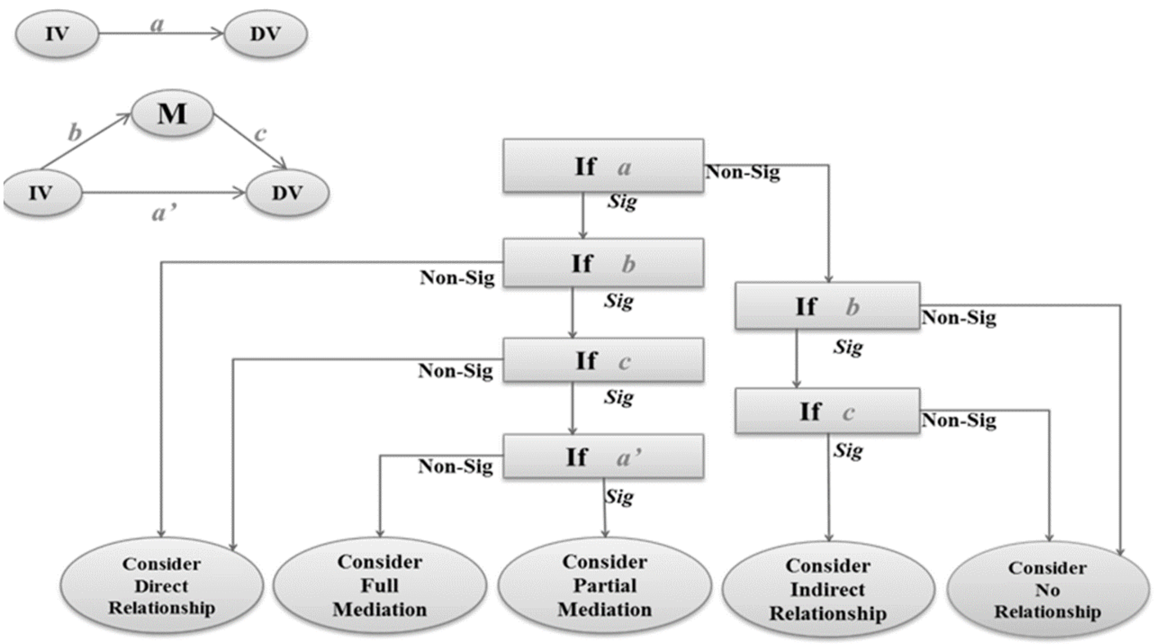
In a statistical analysis, it was found that Risk Perception significantly predicts Strategic Thinking) (see Table 4.11). The critical ratio for this prediction was -2.713 ($p = 0.007$). In practical terms, it means that the regression weight for risk perception in predicting strategic thinking is significantly different from zero at the 0.01 level (two-tailed), providing support for H3. There is an inverse relationship where strategic thinking increases, and risk perception decreases. When decision-makers perceive a situation as risky, they tend to focus more defensively on the short-term. If the risk is low, folks engage more in long-term strategic thinking, planning for the future and considering innovation to achieve their goals. Additionally, $R^2 = -0.115$, unexpectedly indicating a negative relationship between risk perception and strategic thinking. Specifically, when risk perception increases by 1 standard deviation, strategic thinking decreases by 0.115 standard deviations.

4.8.2 Examining Mediation Effect Hypothesis

The mediation analysis was employed to assess the mediating role of Risk Perception on the relationship between Covid-19 Knowledge as the independent variable and Strategic Thinking as the dependent variable H4. Correlation statistics were utilized to investigate this mediation effect (Mathieu & Taylor, 2006). To test the covariance relationships among the IV, potential M, and DV, a decision tree framework proposed by Mathieu and Taylor (2006) was followed. Figure 4.3 illustrates this framework.

Figure 4.3

Decision Tree for Evidence Supporting Different Intervening Effects (Mathieu & Taylor, 2006)



According to the mediation framework, to establish significant mediation, it is essential that all three correlations among the three variables (referred to as paths a, b, and c) must be statistically significant (Baron & Kenny, 1986; Mathieu & Taylor, 2006). If any of these correlations lack statistical significance, significant mediation becomes impossible. Upon the presence of significant relationships among these variables (paths a, b, and c), when the direct effect of the IV on the DV in path 'a' is not statistically significant, the M functions as a full mediator. Conversely, when the direct effect is significant, the mediation is considered partial. In the absence of either full or partial mediation, the relationship between the IV and DV can be classified as direct, indirect, or nonexistent.

Specifically, when there is no significant indirect effect of the independent variable on the dependent variable through the mediating variable, it occurs when path "a" lacks significance while paths "b" and "c" are significant. On the other hand, if path "a" is significant, but paths "b" or "c" are not, there is only a direct effect between the independent variable and the dependent variable. Finally, in the absence of a significant relationship in path "a" and the subsequent absence of significance in paths "b" or "c," there is no discernible relationship between the independent variable and the dependent variable. To assess the mediation effect and its degree, the significance of the regression coefficients between the IV and DV was evaluated using bootstrapping with 2000 replications. The results pertaining to hypothesis H4 can be found in Table 4.12.

Table 4.12

Results of Examining Mediation Effect

IV = CV-19K DV = SST M = RPS	Standardized Effect
Total Effect of CV-19K on SST without RPS (path a)	.795** (p=0.002)
Direct Effect of CV-19K on SST with RPS (path a’)	.809** (p=0.002)
Indirect Effect of CV-19K on SST through RPS (path bc)	-.014* (p=0.019)
Effect of CV-19K on RPS (path b)	.126* (p=0.039)
Effect of RPS on SST (path c)	-.115** (p=0.004)
Mediation Effect	Yes
Degree of Mediation	Partial
Hypothesis Result	H4: Supported

Note. *, **, ***: Contribution is significant at the 0.05, 0.01 and 0.001 level (2-tailed).

H4: ***Risk Perception mediates the relationship between Covid-19 Knowledge and Strategic Thinking***

The research showed that there exists a significant positive relationship between CV-19K and SST when RPS is not considered (Table 4.12; standardized total effect = 0.795, p = 0.002), demonstrating that the total effect of CV-19K on SST is statistically significant at the 0.01 level. This positive relationship persists even after incorporating RPS into the analysis, as indicated by a standardized direct effect of 0.809 and a p-value of 0.001, confirming the statistical significance at the 0.01 level.

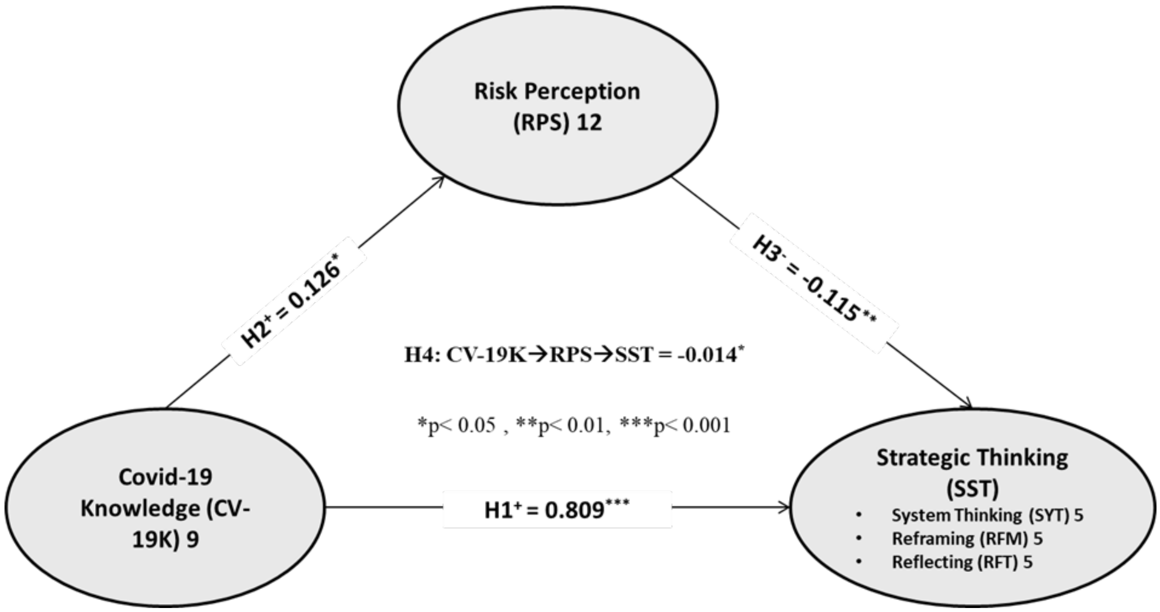
The study also revealed that the impact of CV-19K as an independent variable on RPS as a mediator (path b) is positive and statistically significant at the 0.05 level (standardized effect = 0.126). In contrast, RPS as a mediator affecting Strategic Thinking (SST) as the dependent variable (path c) is negative and statistically significant at the 0.01 level (standardized effect = -0.115). These findings suggest that RPS acts as a partial mediator in the relationship between CV-19K and SST, supported by the statistical significance of paths a, a', b, and c, confirming hypothesis H4. Additionally, CV-19K exerts a significant indirect negative effect on SST through RPS, with a standardized indirect effect of -0.014 (p= < 0.05).

4.8.3 Results of Structural Model

Figure 4.4 illustrates the outcomes of investigating the direct and mediation effect hypotheses within the structural model, displaying standardized coefficients.

Figure 4.4

Results of the Examined Direct and Mediation Effects Hypotheses



4.9 Summary

The results of the analysis revealed that Covid-19 knowledge had significant positive effects on strategic thinking and risk perception while risk perception had a significant negative effect on strategic thinking. Consequently, the direct hypotheses H1, H2, and H3 were supported. Furthermore, the mediation analysis demonstrated that risk perception partially mediated the positive relationship between Covid-19 knowledge and strategic thinking. Specifically, Covid-19 knowledge had a significant negative indirect effect on strategic thinking through risk perception. This finding provided support for hypothesis H4.

CHAPTER 5

DISCUSSION, IMPLICATION, LIMITATIONS, AND CONCLUSION

5.1 Overview

In this chapter, the dissertation is structured into four sections. Firstly, it outlines the primary objective of the research. Subsequently, the second section delves into examining the outcomes discussed in Chapter 4 and their connections to relevant scholarly literature. Following this, the third segment scrutinizes the implications of these findings for both research and organizational contexts. Lastly, the fourth part critically assesses the study's limitations and proposes directions for future research endeavors.

Understanding the significance of Covid-19 in the current business context is crucial. With widespread vaccine availability, health organizations have witnessed a relaxation in health standards. Utilizing the insights gained from studying Covid-19 is vital. It prompted healthcare decision makers to realize the necessity for fresh strategies in key areas like obtaining information, integrating it, storing, sharing, and applying it. This is essential for creating and maintaining a competitive edge within an organization. Activities related to knowledge management significantly enhance an organization's core competitiveness.

This study primarily focuses on the relationship between Covid-19 knowledge and risk perception, vital factors influencing strategic decision-making in healthcare leadership. It examines how mid-level and upper-level managers strategized during the pandemic, particularly in healthcare organizations in the United States. During crises, the roles of managers become crucial as they play a key part in building trust, facilitating effective communication, and ensuring productivity. The research aims to shed light on three key knowledge areas: understanding Covid-19, risk perception, and strategic thinking within healthcare organizations, offering valuable insights for healthcare industry leaders in crisis management. The research's findings are essential for healthcare decision-makers, aiding them in better preparing and adapting strategies for impending crises. Additionally, this study contributes to the academic understanding of how risk perception influences strategic decision-making during crises like Covid-19, offering valuable insights for healthcare leaders and advancing knowledge in the field. The research questions that guide this study are as follows:

1. How does Covid-19 knowledge affect risk perception in relation to strategic thinking?
2. To what extent does risk perception mediate the relationship between Covid-19 knowledge and strategic thinking?
3. Is there a significant direct effect of Covid-19 knowledge on strategic thinking, even after accounting for the mediating effect of risk perception?

To explore these questions, the study employed quantitative approach using SEM to examine the direct relationships between the variables and the role of RPS as a mediator.

5.2 Discussion

In today's ever-evolving businesses, having a thorough understanding of Covid-19 or any crisis situation is imperative for the success of enterprises (Asefa et al., 2020). With the advent and widespread use of vaccinations, leaders and decision-makers within healthcare organizations have been able to gradually ease health-related restrictions that were initially imposed during the early stages of the pandemic. Covid-19 knowledge is important because it got healthcare decision makers to recognize that they needed new strategy. During this period, effective management has played a pivotal role in fostering an environment characterized by transparency, open communication, and sustained productivity (Ding et al., 2020).

In contrast to their counterparts, companies with robust cognitive resources were better equipped to leverage and expand their assets (Hakim et al., 2021). An effective strategy for addressing knowledge gaps involved the implementation of an emergent knowledge strategy that continually emerged as new knowledge became available (Mant et al., 2021). The initial hypothesis postulated a significantly positive impact of Covid-19 knowledge on strategic thinking. The results of hypothesis testing unveiled a positive relationship, with a standardized estimate of Beta standing at 0.809. According to Shahin and Hussein (2020), understanding theories about knowledge is crucial as it provides valuable insights that aid decision makers in forming strategic plans.

This study investigated the significant influence of Covid-19 knowledge on Risk Perception with $R^{2} = 0.126$, $p = 0.001$ significance level. Iorfa et al. (2020) confirmed a significant correlation between understanding of Covid-19 and the perception of the associated risks. Recognizing this connection is crucial, as a deeper comprehension of Covid-19 empowers decision makers to make informed decisions by accurately assessing the risks linked to the virus. This, in turn, promotes effective public health measures.

This outcomes underscore the role of risk perception as a determinant in shaping preventive measures and strategies, particularly in the context of emerging infectious diseases like Covid-19. This observation aligns with Yıldırım and Güler (2020), who emphasize the profound connection between an individual's capacity to encourage precautionary behavior and their perceived risk of contracting a disease. The link between a person's ability to promote preventive actions and their perception of the risk of getting a disease is crucial. When individuals recognize the seriousness of the risk, it often motivates them to actively engage in precautionary behaviors to protect themselves. Furthermore, in accordance with the Health Belief Model (Carico et al., 2020), individuals typically require a clear understanding of the risks associated with a disease before actively participating in preventive measures.

Iorfa et al. (2020) discovered that the connection between knowing about Covid-19 and actually taking preventive measures is influenced by how people perceive the risks involved. For instance, a study on the 2014 middle east respiratory disease outbreak among Saudi and non-Saudi pilgrims found that a comprehensive understanding of the disease's etiology, symptoms, and the individual perception of its risk were closely linked to precautionary behavior (Klinke & Renn, 2002). Teh et al. (2019) argued that information significantly influences cautious behavior through the prism of risk perception. Conversely, individuals who considered themselves well-informed but did not perceive the disease as a substantial risk were less inclined to adopt preventive measures. This study offers substantial evidence in favor of the Health Belief Model's assertion that risk perception plays a pivotal role in predicting health behavior (Carico et al., 2020).

Emotions, trust, and intuition also play crucial roles in shaping threat perception, particularly in situations marked by uncertainty (Rayani et al., 2021). Notably, individuals with positive risk perceptions and strong dispositional optimism may underestimate the severity of threats and avoid seeking additional medical information (Asefa et al., 2020).

However, successful implementation of corporate strategy in healthcare requires effective communication, alignment of organizational departments with enterprise-level plans, execution of strategic initiatives, and management of competency development and employee incentives in line with strategic objectives (Wang et al., 2022; Shahin & Hussien, 2020). In response to the Covid-19 crisis, organizations established task forces and developed crisis resolution strategies (Maude et al., 2021). Effective strategies in the healthcare industry necessitate involvement of experts, intersectoral collaboration, scalability of solutions, proactive federal policy management, and regulatory reforms (Maude et al., 2021).

Middle-level managers serve as crucial intermediaries between operational personnel and senior management, responsible for interpreting and communicating organizational strategies (Yldrm & Güler, 2020). They are instrumental in implementing decisions and providing information to senior management (Teh et al., 2019). The Covid-19 outbreak has had unintended consequences across various sectors, emphasizing the need for systems thinking to manage healthcare services effectively, considering both quality and safety (Carico et al., 2020; Lohiniva et al., 2022). Systems thinking provides insights into how system elements interact over time, identifies reasons for system failures, and informs effective problem-solving measures (Faasse & Newby, 2020). A comprehensive understanding of system complexity is essential for addressing health challenges (Alzoubi et al., 2020).

Risk Perception was found to partially mediate the relationship between Covid-19 Knowledge and Strategic Thinking, resulting in a significant indirect negative impact of Covid-19 on Strategic Thinking (Mbachu et al., 2020). Healthcare decision-makers' strategic thinking is influenced by both Covid-19 knowledge and risk perception (Mbachu et al., 2020). Healthcare workers face various job-related risks during a pandemic, including physical and emotional health risks (Vuong et al., 2022), emphasizing the need for effective risk management and support.

It was also observed that specialist doctors and mid to upper-level managers in state hospitals had higher knowledge scores, while mid- to upper-level managers exhibited greater preventive behavior (Lohiniva et al., 2022). Gender differences were noted in preventive behaviors, with women being more proactive, consistent with previous research findings (Lohiniva et al., 2022). However, the utilization of knowledge in driving preventive behaviors appeared to be suboptimal, possibly due to workforce size and insufficient support for safety equipment.

In conclusion, the study findings underscore the multifaceted relationship between risk perception, knowledge, and strategic thinking in the context of healthcare crises, emphasizing the importance of effective communication, intersectoral collaboration, and systems thinking for managing complex challenges. Additionally, the role of middle-level managers as crucial decision implementers and information providers in healthcare organizations is highlighted, along with the need for ongoing evaluation and support for preventive behaviors.

5.3 Implication of the Study

According to Arslanca et al. (2021), the way work is organized in different industries has undergone significant changes due to the pandemic. The healthcare industry, in particular, has faced substantial challenges in maintaining healthcare services and treating infected individuals (Arslanca et al., 2021; Faasse & Newby, 2020). Healthcare managers played a crucial role in coordinating activities and ensuring the well-being of their staff members during this crisis (Arslanca et al., 2021). However, more research is needed to understand the factors influencing risk perception and the impact of Covid-19 knowledge on healthcare decision-makers, especially regarding the mediating role of risk perception (Arslanca et al., 2021).

Arslanca et al. (2021) emphasized the importance of promoting accurate knowledge of Covid-19 through educational campaigns to encourage precautionary behavior. This is essential, given the prevalence of misinformation and conspiracy theories surrounding the pandemic (Arslanca et al., 2021). Healthcare organizations have had to adapt their business models to survive the pandemic, with varying responses ranging from a focus on Covid-19 mitigation to maintaining core competencies and exploring new revenue streams (Faasse & Newby, 2020). Successful healthcare organizations have demonstrated adaptability, resource utilization, and flexibility in the face of adversity (Faasse & Newby, 2020).

The mental health and exposure to hazards can significantly influence how healthcare workers perceive risk (Ding et al., 2020). Understanding the knowledge, attitudes, and behaviors of healthcare workers is crucial for pandemic preparedness (Ding et al., 2020). Healthcare managers have had to implement changes in organizational practices, such as halting less urgent medical procedures and creating safe environments for patients (Atchison et al., 2020).

The pandemic has pushed healthcare administrators beyond their traditional roles, necessitating strategic planning, innovation, and risk perception (Arslanca et al., 2021). Risk awareness campaigns, in alignment with the Health Belief Model, should effectively communicate the health risks associated with certain activities, enhancing the perceived seriousness of the disease's hazards (Carico et al., 2020). Public education on disease origins and risks is crucial in controlling outbreaks (Carico et al., 2020).

The findings of this study and previous research highlight the need for further investigation into the factors influencing healthcare decision-makers' strategies during crises (Arslanca et al., 2021). Such research serves as a preventive measure against future pandemics and endemics. While healthcare workers possess substantial knowledge about Covid-19, there is room for improvement in their adoption of preventive behaviors (Arslanca et al., 2021). Vigilance in monitoring and responding to preventive practices during the pandemic is essential (Arslanca et al., 2021). Governments should issue orders based on pandemic response practices while simultaneously promoting preventive behaviors, enhancing risk perception, and providing online education to healthcare professionals to slow down the spread of Covid-19 (Arslanca et al., 2021; Faasse & Newby, 2020)

5.4 Limitations and Future Research

This study has several limitations that must be acknowledged. Firstly, due to the online nature of the survey, which required access to a computer, tablet, or smartphone, there is a potential for selection bias (Smith et al., 2020). Securing access to online medical decision workers for the purpose of conducting surveys proved to be a challenging endeavor, demanding an extended duration for recruitment efforts. Moreover, the endeavor necessitated the utilization of high-cost online platforms, including but not limited to cloud research, Prolific, and Qualtrics, as means of reaching this specific demographic. Additionally, the majority of healthcare organizations in the sample were based in the United States, limiting the generalizability of the findings to a global context

(Jones et al., 2021). Moreover, the exclusive focus on healthcare company administrators in a specific region further restricts the generalizability of the study's findings (Brown et al., 2019).

Furthermore, the study's reliance on a relatively small sample size may affect the reliability of the results (Johnson et al., 2018). The accuracy of the findings also depends on the participants' honesty and recollection (Davis et al., 2017). Therefore, it is important to consider this study as preliminary in nature (Anderson et al., 2020). Single population, culture, research methodology and location are also limitations. Nonetheless, the conclusions drawn from this study can still be valuable for guiding effective risk communication and learning strategies in the context of an organization's response to an epidemic (Adams et al., 2019).

Additionally, the study does not differentiate between the perspectives of mid-level and upper-level managers regarding the risks associated with their chosen strategies impacting the health behaviors of their employees (Hakim et al., 2021). Research by Hakim et al. (2021) highlights the significance of healthcare professionals' mental health and their exposure to hazards in shaping risk perceptions. Therefore, it is imperative to investigate the knowledge, attitudes, and behaviors of healthcare workers in order to develop effective strategies for pandemic preparedness (Hakim et al., 2021).

Furthermore, future research should aim to explore how individuals' health behaviors evolve over time, as individual behavior plays a crucial role in maintaining a flattened epidemic curve, especially as vaccines become more widely available (Taylor et al., 2022). This will provide a more comprehensive understanding of the dynamics between strategy adoption, risk perception, and health behavior change in crisis scenarios (Smith et al., 2020).

Future research in the context of a dissertation paper may delve into the imperative realm of communication strategies aimed at perpetually enhancing knowledge and risk perception among healthcare stakeholders, particularly owners. This research could not only further investigate the intricacies of mediating effects, building upon the notable successes already achieved, but also explore various alternative configurations of relationships, including assessing direct effects and the potential moderating role of risk perception within the construct framework. Additionally, the inclusion and analysis of control variables such as age, gender, and education could serve to deepen our understanding of the dynamic interplay between these factors and the overarching communication strategies required to navigate the ongoing challenges posed by the pandemic. This multifaceted research endeavor promises to yield invaluable insights and recommendations essential for enhancing healthcare preparedness and resilience in the face of unprecedented global health crises.

Future research should focus on tailoring evidence-based interventions and programs to address barriers with the ultimate aim of enhancing health equity in pandemic response efforts, as suggested by Erchick et al.(2022).

The study provides valuable preliminary insights into the relationships between strategy adoption, risk perception, and pandemic outcomes, it is essential to acknowledge its limitations in terms of sampling, financial implication, generalizability, and the need for further investigation into the perspectives of different managerial levels and healthcare workers. Future research should aim to address these limitations and provide a more comprehensive understanding of the complex dynamics involved in pandemic prevention and crisis management

5.5 Conclusion

Healthcare institutions are urged to take proactive measures to prepare for crises such as Covid-19, acknowledging the formidable challenges of pandemics or other such permanent shocks. In the face of daunting financial constraints, healthcare management is expected to maintain operational continuity. Adaptive strategies, including strategic plan revisions, are essential for healthcare leadership to navigate changing circumstances.

Strategic thinking and planning play a crucial role in achieving multiple objectives, particularly in the context of pandemic response and healthcare resilience. In times of uncertainty, organizations may need to realign their corporate strategies to ensure resilience and adaptability. By embracing strategic approaches, organizations can foster innovation, refine existing business models, and enhance profitability while continuing to serve their target market. Consequently, organizations have developed comprehensive plans, implemented management initiatives, and leveraged technological solutions to effectively manage information and ensure sustainability in the face of the disruptive impact of Covid-19.

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APPENDICES

APPENDIX A

IRB APPROVAL

UNIVERSITY OF DALLAS Institutional Review Board

IRB00007703 FWA 00016247 IORG0006409

April 11, 2023

Franklyn Echemah
Satish & Yasmin Gupta College of Business
University of Dallas
Irving, TX 75062

RE: IRB approval of proposal # 2023021

Dear investigator:

Thank you for submitting your research proposal for prior approval by the Institutional Review Board (IRB). Your proposal was reviewed under the procedure for expedited review, as it poses minimal risk for participants using surveys with adults. You indicate that steps will be taken to procure informed consent and protect participants' identities. The reviewer(s) recommended approval of your request to complete the research described in your proposal under the conditions stated above.

As you complete your research, please keep in mind that substantive changes to the research method, participant population or project end date will require IRB review, and that any participant injuries or complaints must be reported to the IRB at the time they occur. The IRB policies require that you provide an annual report of the progress of this research project, or a report upon completion, whichever occurs first.

On behalf of the members of the IRB, I wish you success in this project.

Gilbert Garza, Ph.D.
IRB Chair

1845 East Northgate Drive, Irving, TX 75062-4736

APPENDIX B

SURVEY INSTRUMENT

UNIVERSITY OF DALLAS

CONSENT TO PARTICIPATE IN A RESEARCH STUDY

University of Dallas

Below is a description of the research procedures and an explanation of your rights as a research participant. In accordance with the policies of the University of Dallas, you are asked to read this information carefully.

The purpose of this study is to help researchers address knowledge of pandemics coupled with risk and their impact on strategic thinking in healthcare organizations. Strategic thinking involves considering different courses of action and their potential outcomes. Research on strategic thinking related to Covid-19 knowledge can help mid-managers and business decision-makers make informed decisions about responding to the pandemic and balancing their business decisions' health and economic impacts. Your participation is completely voluntary, and if you begin participation and choose not to complete it, you are free to not continue without any consequences.

If you agree to be in this study, you will be asked to do the following things:

- Confirm that you are at least 18 years of age.
- Confirm that you voluntarily agree to complete an online multiple-choice survey.
- Be willing to take 10 minutes or less to answer all questions honestly, as there are no right or wrong answers.

Appendix B. Continued

- Selecting the button that best corresponds to your response after reading each question or statement.
- Scroll down the page to answer all the questions if needed, and select NEXT to continue after each page.
- Complete the survey in one sitting.

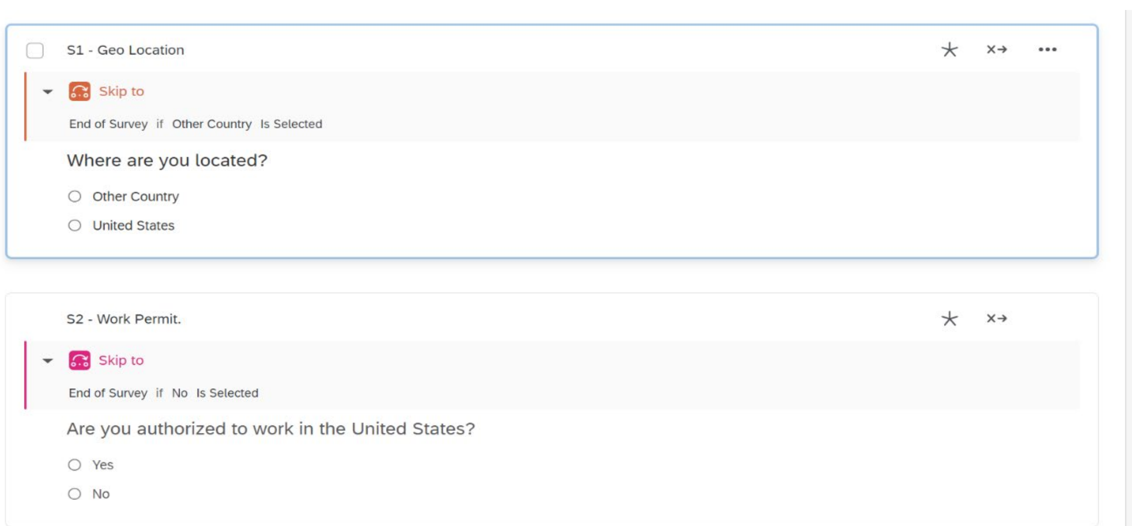
There are no known risks to this study other than becoming a little tired of answering the questions. If this happens, you are free to take a break and return to the survey to finish it, or you can discontinue participation without any problems.

Because you will not be providing any clues to your identity, you can be assured that all your provided responses to the questions are anonymous. If you need to ask questions about this study, you can contact the principal researcher, Franklyn Echemah, at fechemah@udallas.edu, or if you have questions about your rights as a participant, you may contact the Chair of the University of Dallas IRB, Dr. Gilbert Garza, at (972) 721-5366 or garza@udallas.edu.

I have read and understood what has been explained to me, If I choose to participate in this study, I will click "Yes" in the box below and proceed to the survey. If I choose not to participate, I will click "No" in the box.

○ Yes, I choose to participate in this study

○ No, I choose to not participate in this study


S1 - Geo Location

Skip to

End of Survey if Other Country Is Selected

Where are you located?

○ Other Country

○ United States

S2 - Work Permit.

Skip to

End of Survey if No Is Selected

Are you authorized to work in the United States?

○ Yes

○ No

Appendix B. Continued

S3- Sector

Skip to

End of Survey if Non-Healthcare Organizations Is Selected

Skip to

End of Survey if Non-Healthcare Organizations Is Selected

What best describes the organizational sector that you work in?

- ○ Healthcare Organizations
- ○ Non-Healthcare Organizations

S4 - Job Title

Skip to

End of Survey if Other Is Selected

What is your current job title?

- ○ Upper-Level Manager
- ○ Mid-Level Manager
- ○ Other

Marker Variable

CMV

Please read each statement carefully and indicate how much you agree with each statement. Please be honest as there are no right or wrong answers. Often, the best approach is to select the first response that comes to your mind. Thinking about your attitude toward color blue.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
Blue is a beautiful color	○	○	○	○	○	○	○
Blue is a lovely color	○	○	○	○	○	○	○
Blue is a pleasant color	○	○	○	○	○	○	○
The color blue is wonderful	○	○	○	○	○	○	○
Blue is a nice color	○	○	○	○	○	○	○
I think blue is a pretty color	○	○	○	○	○	○	○
I like the color blue	○	○	○	○	○	○	○

Appendix B. Continued

IV- Covid-19 Scales

CV-19K

The following statements are about your knowledge of Covid-19. Indicate the extent to which you agree with each statement statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree or Disagree	Somewhat Agree	Agree	Strongly Agree
COVID-19 is a contagious disease.	○	○	○	○	○	○	○
The primary cause of COVID-19 is a bacterium.	○	○	○	○	○	○	○
The incubation period of COVID-19 is 2 to 3 days.	○	○	○	○	○	○	○
The main clinical symptoms of COVID-19 are fever, fatigue, dry cough, and headache.	○	○	○	○	○	○	○
Aspirin is the definitive treatment for COVID-19	○	○	○	○	○	○	○
The disease can be transmitted directly through contact with infected surfaces	○	○	○	○	○	○	○
The disease can be transmitted directly through contact with infected individuals (handshaking, hugging, and kissing)	○	○	○	○	○	○	○
To prevent the infection, people should avoid going to crowded places such as crowded restaurant, large parties, football stadium, church, and political rallies.	○	○	○	○	○	○	○
Washing your hands, covering nose and mouth, and cleaning surfaces, and being cautious around people with COVID-19 can help in the prevention of COVID-19 transmission	○	○	○	○	○	○	○

IMC_A

IMC_A

Please ignore the answer choices below and simply click on the NEXT button.

Page Break

IMC_A1

What is your favorite color

- ○ Yellow
- ○ Orange
- ○ White
- ○ Other

Appendix B. Continued

IMC_A1_R

Display this question

If What is your favorite color Yellow Is Selected

Or What is your favorite color Orange Is Selected

Or What is your favorite color White Is Selected

Or What is your favorite color Other Is Selected

You have failed the attention check.

Although that does not disqualify you, close attention will be paid to your responses to ensure that the HIT has been completed to reasonable satisfaction. If you fail again, you will be exited from the survey.

Data quality is extremely important for the success of the project. Please pay more attention to the remaining questions.

Click **OK** if you wish to continue. Otherwise, you may exit the survey.

○ 

MV - RPS

RP_1

The following statements are about your risk of getting Covid-19 or giving it to someone else. Indicate how safe you feel in each of these situations.

	Extremely Safe	Safe	Somewhat safe	Unsure	Extremely Unsafe	Unsafe	Somewhat Unsafe
Providing services in the client's home	○	○	○	○	○	○	○
Attending a gathering of more than 10 people?	○	○	○	○	○	○	○
Attending a gathering of more than 100 people?	○	○	○	○	○	○	○
Providing services in the office	○	○	○	○	○	○	○

Appendix B. Continued

Providing services in the emergency room	○	○	○	○	○	○	○
Returning to work after the outbreak	○	○	○	○	○	○	○
Working outdoors in the crowd	○	○	○	○	○	○	○
Working indoors in the crowd	○	○	○	○	○	○	○
Visiting friends or relatives in their homes and staying indoors	○	○	○	○	○	○	○
Visiting Friends or relatives in their homes and staying outdoors	○	○	○	○	○	○	○
Visiting elderly relatives at home or old people's home	○	○	○	○	○	○	○
Visiting elderly relatives at the hospital	○	○	○	○	○	○	○

DV - STS

DV_SYT

Please read each statement carefully and think of how it relates to system thinking in business strategy. Indicate how much you agree with each statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I look for fundamental long-term proactive measures.	○	○	○	○	○	○	○
I look for adaptive changes in the structure that could lead to significant improvement	○	○	○	○	○	○	○
I look at the "Big Picture" in the information available before examining the details?	○	○	○	○	○	○	○
I investigate the cause before taking action.	○	○	○	○	○	○	○
I try to understand how the facts in the situation relate to each other.	○	○	○	○	○	○	○

DV_RFM

Please read each statement carefully and think of how it relates to reframing business strategy. Indicate how much you agree with each statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I ignore my past experiences when trying to understand situations presented to me	○	○	○	○	○	○	○
I ignore past decisions when considering current similar situations	○	○	○	○	○	○	○
I usually find only one explanation for the way things work	○	○	○	○	○	○	○
I create a plan to solve a problem before considering other viewpoints	○	○	○	○	○	○	○
I decided upon a point of view before I identify solutions to a problem	○	○	○	○	○	○	○

Appendix B. Continued

DV-RFT

Please read each statement carefully and think of how it relates to reflecting on business strategy. Indicate how much you agree with each statement.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat agree	Agree	Strongly Agree
I reconstruct an experience in my mind to understand how I feel about it	○	○	○	○	○	○	○
I reconstruct an experience in my mind	○	○	○	○	○	○	○
I consider how I could have handled the situation after it was resolved	○	○	○	○	○	○	○
I stop and think about why I succeeded or failed	○	○	○	○	○	○	○
I try to understand how a problem worked out after it was resolved	○	○	○	○	○	○	○
I am paying attention to the statements	○	○	○	○	○	○	○

Demographics

Demo

Please answer the following general questions about yourself. Remember, none of this information is tied to your identity and all answers are confidential and anonymous.

D1 - Gender

What is your gender?

- ○ Male
- ○ Female
- ○ other/prefer not to say

D2 - Age

What is your age?

Appendix B. Continued

D3 - Tenure

How many years have you worked at your company?
Please select 0, if you have worked less than a year at your company.

D4 - Education.

What is your level of education?

- No Education Degree
- High School or Equivalent
- Bachelor's Degree
- Master's Degree
- Professional Degree
- Doctorate Degree

D5 - Race

Which best describes your race/ethnicity?

- African American or Black
- American Indian/Other Native American
- Asian or Pacific Islander
- Caucasian or White (other than Hispanic)
- Hispanic
- Other

Q23

What is your job title?

Q24

In light of the Covid-19 pandemic, how has the process of making strategic decisions evolved?

Q24

How did you access the survey? (For Survey Circle users (www.surveycircle.com): The Survey Code is: 2146-RXK9-3YWL-XHRV)

- LinkedIn
- Facebook / Instagram
- Email
- Survey Circle
- Other

Import from library | Add new question

Add Block

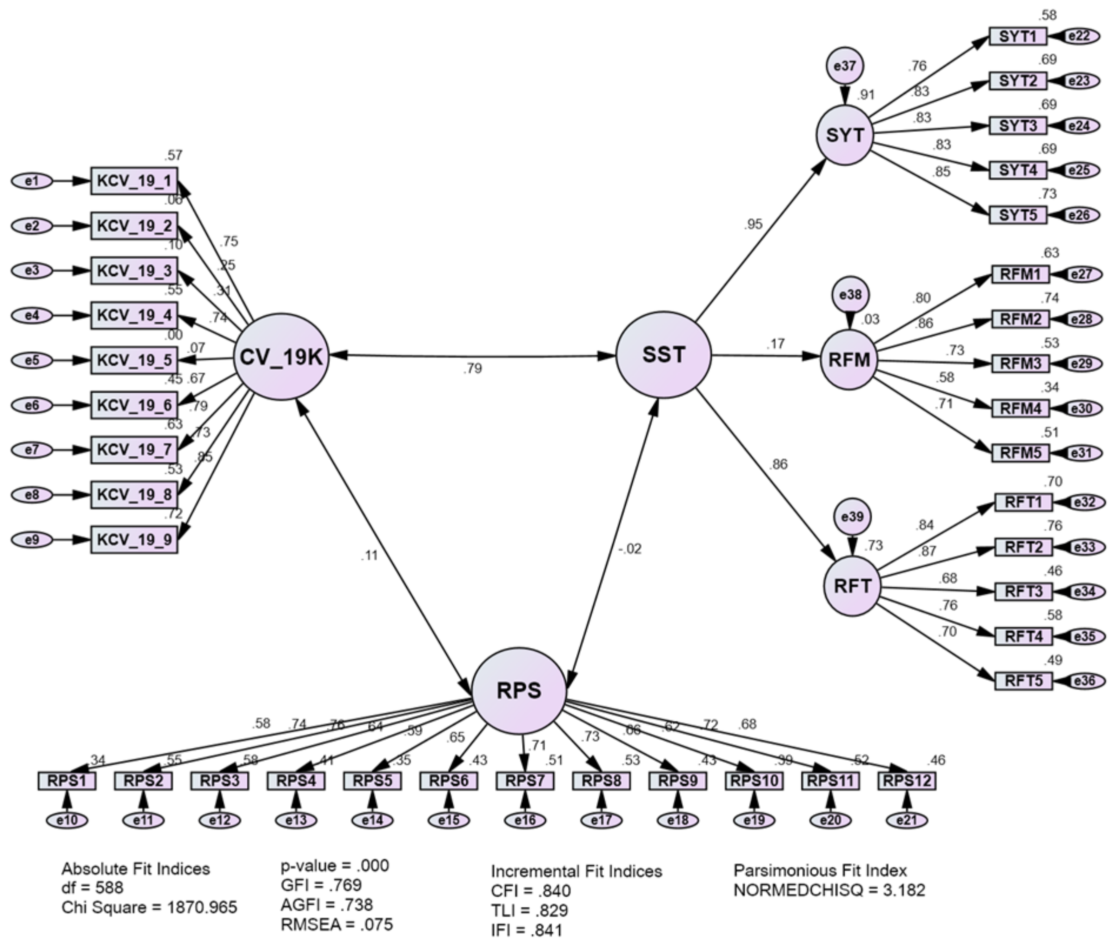
End of Survey

We thank you for your time spent taking this survey.

Your response has been recorded.

APPENDIX C

ALL EXOGENOUS AND ENDOGENOUS VARIABLES TOGETHER WITH THEIR RELATIVE ESTIMATION ERRORS



APPENDIX D

Observations farthest from the centroid (Mahalanobis distance) Number of variables in the model = 81. Max (D^2) / (no. variables) = 118.708 / 81 = 1.409 which is < 3.5 → No Multivariate Outliers.

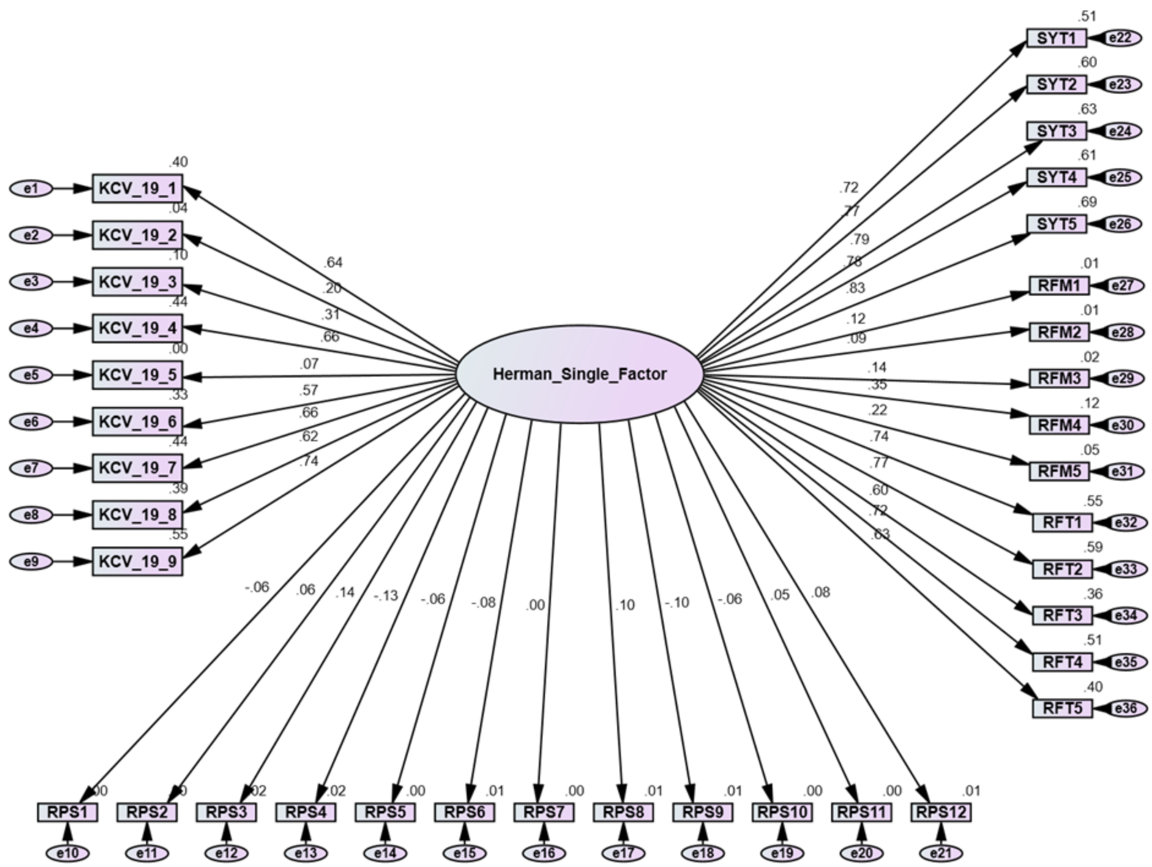
Observation number	Mahalanobis d-squared	p1	p2
390	118.708	.000	.000
389	107.499	.000	.000
385	105.449	.000	.000
388	104.811	.000	.000
383	97.636	.000	.000
386	94.544	.000	.000
387	93.294	.000	.000
384	90.545	.000	.000
381	88.891	.000	.000
380	83.676	.000	.000
373	80.928	.000	.000
379	78.881	.000	.000
378	78.691	.000	.000
382	77.903	.000	.000
367	77.587	.000	.000
366	74.758	.000	.000
374	74.377	.000	.000
376	73.383	.000	.000
363	72.819	.000	.000
361	72.082	.000	.000
375	72.025	.000	.000
360	70.905	.000	.000
370	70.730	.000	.000
377	70.376	.001	.000
359	68.616	.001	.000
362	67.173	.001	.000
365	66.590	.001	.000
371	65.231	.002	.000
348	64.941	.002	.000
345	64.802	.002	.000
354	64.794	.002	.000
369	64.607	.002	.000

Observation number	Mahalanobis d-squared	p1	p2
351	64.595	.002	.000
323	62.383	.004	.000
328	61.881	.005	.000
364	60.734	.006	.000
297	60.537	.006	.000
344	60.261	.007	.000
341	59.932	.007	.000
372	59.695	.008	.000
330	59.579	.008	.000
318	59.364	.008	.000
357	59.001	.009	.000
290	58.622	.010	.000
355	58.534	.010	.000
309	58.491	.010	.000
322	58.402	.011	.000
321	58.228	.011	.000
352	57.833	.012	.000
368	57.737	.012	.000
270	57.684	.012	.000
350	57.369	.013	.000
342	56.191	.017	.000
338	55.832	.019	.000
333	54.900	.023	.000
340	54.851	.023	.000
358	54.830	.023	.000
343	54.794	.023	.000
291	54.548	.024	.000
306	54.389	.025	.000
280	54.389	.025	.000
347	54.358	.025	.000
307	53.894	.028	.000
268	53.278	.032	.000
311	53.218	.032	.000
346	53.012	.034	.000
292	52.752	.035	.000
325	52.144	.040	.000
258	52.000	.041	.000

Observation number	Mahalanobis d-squared	p1	p2
324	51.927	.042	.000
353	51.325	.047	.000
339	51.212	.048	.000
336	51.150	.049	.000
305	51.104	.049	.000
335	50.966	.050	.000
213	49.910	.062	.000
319	49.667	.064	.000
301	49.617	.065	.000
296	49.438	.067	.000
243	49.328	.069	.000
332	49.033	.072	.000
207	48.934	.074	.000
327	48.405	.081	.000
289	48.346	.082	.000
314	48.254	.083	.000
334	48.214	.084	.000
233	48.084	.086	.000
245	48.078	.086	.000
272	48.028	.087	.000
299	47.938	.088	.000
276	47.346	.098	.000
241	46.989	.104	.000
294	46.758	.108	.000
304	46.618	.111	.000
331	46.586	.111	.000
316	46.550	.112	.000
329	46.162	.119	.000
308	46.086	.121	.000
260	46.053	.122	.000
217	45.923	.124	.000

APPENDIX E

HERMAN'S SINGLE FACTOR MODEL



Absolute Fit Indices
df = 594
Chi Square = 5180.540

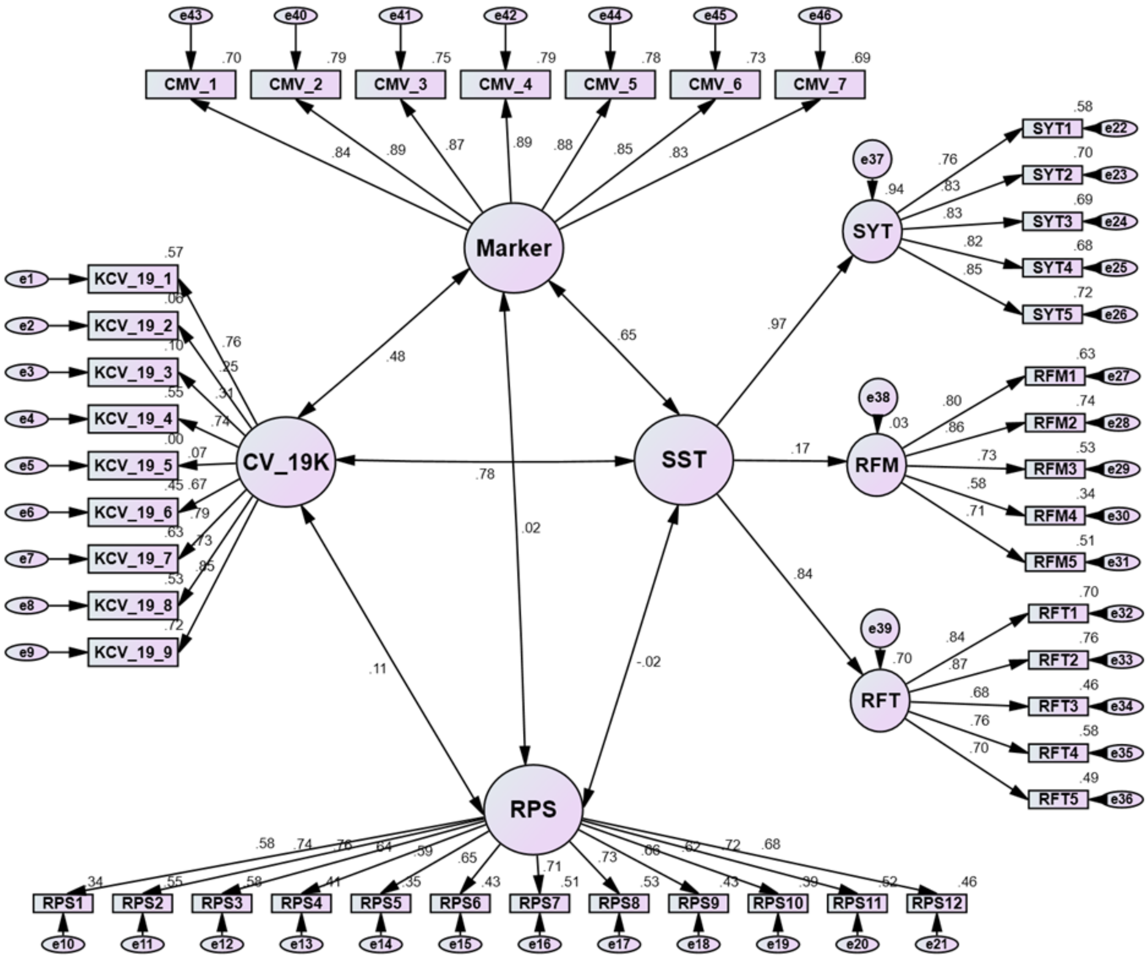
p-value = .000
GFI = .419
AGFI = .349
RMSEA = .141

Incremental Fit Indices
CFI = .429
TLI = .395
IFI = .432

Parsimonious Fit Index
NORMEDCHISQ = 8.721

APPENDIX F

CFA WITH MARKER VARIABLE MODEL



Absolute Fit Indices
df = 851
Chi Square = 2382.417

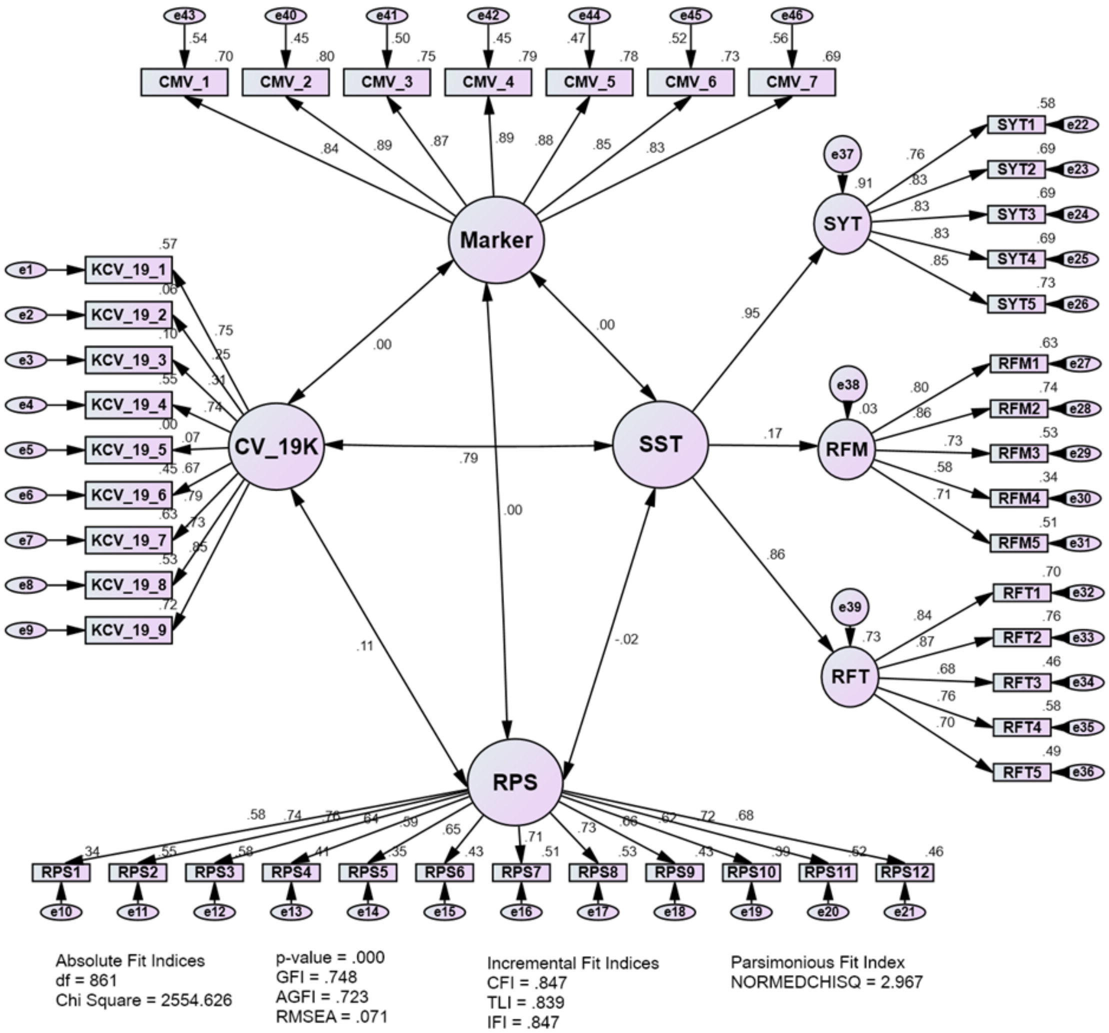
p-value = .000
GFI = .759
AGFI = .732
RMSEA = .068

Incremental Fit Indices
CFI = .861
TLI = .853
IFI = .862

Parsimonious Fit Index
NORMEDCHISQ = 2.800

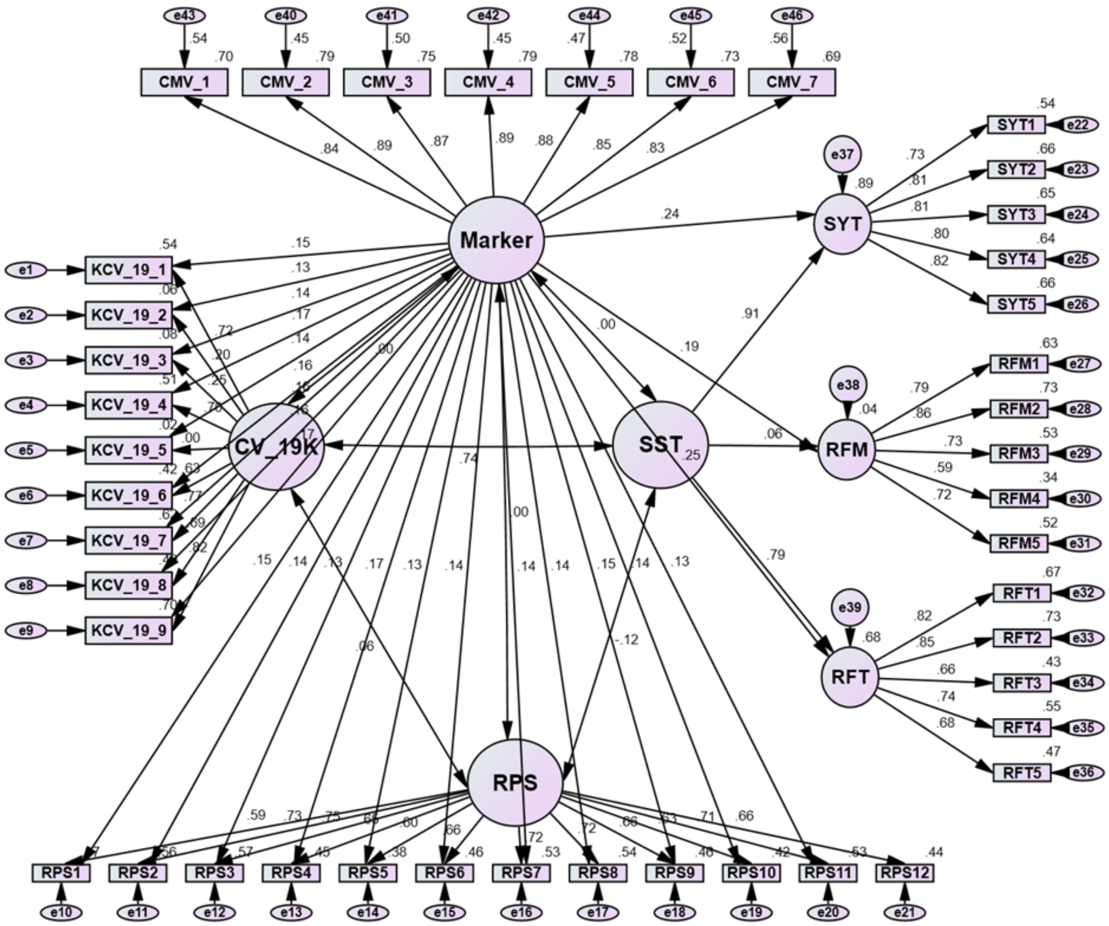
APPENDIX G

BASELINE MODEL



APPENDIX H

CONSTRAINED MODEL



Absolute Fit Indices
df = 860
Chi Square = 2501.614

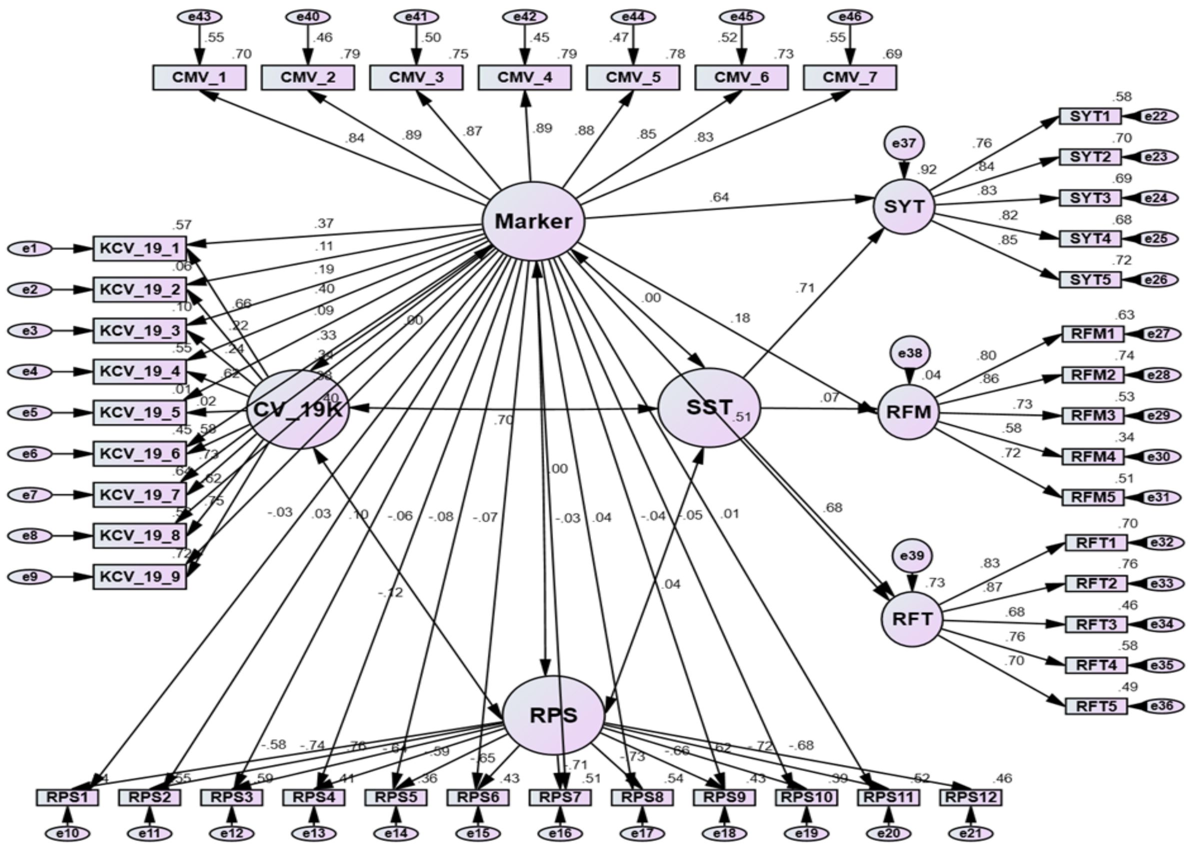
p-value = .000
GFI = .748
AGFI = .723
RMSEA = .070

Incremental Fit Indices
CFI = .851
TLI = .844
IFI = .852

Parsimonious Fit Index
NORMEDCHISQ = 2.909

APPENDIX I

UNCONSTRAINED MODEL



Absolute Fit Indices
df = 838
Chi Square = 2346.195

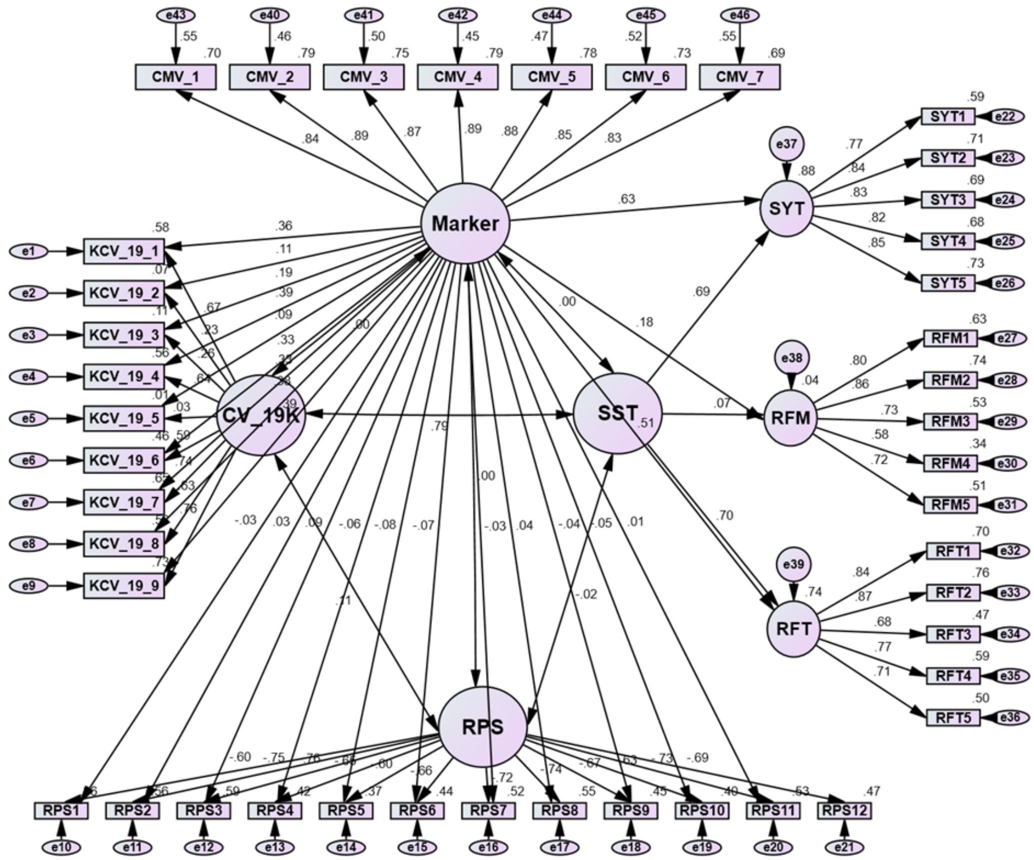
p-value = .000
GFI = .763
AGFI = .732
RMSEA = .068

Incremental Fit Indices
CFI = .863
TLI = .853
IFI = .864

Parsimonious Fit Index
NORMEDCHISQ = 2.800

APPENDIX J

RESTRICTED MODEL



Absolute Fit Indices
df = 841
Chi Square = 2390.062

p-value = .000
GFI = .760
AGFI = .730
RMSEA = .069

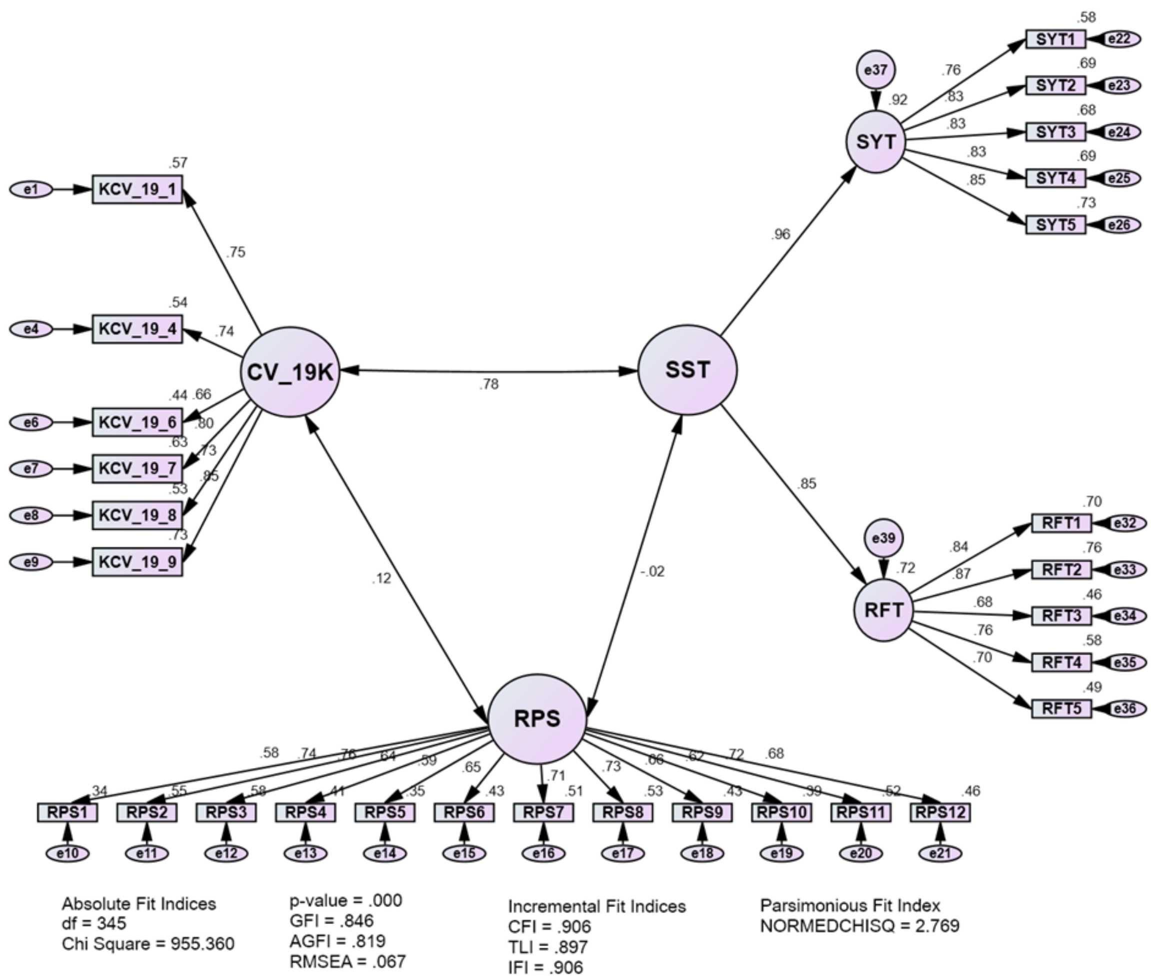
Incremental Fit Indices
CFI = .860
TLI = .849
IFI = .860

Parsimonious Fit Index
NORMEDCHISQ = 2.842

APPENDIX K

2ND CFA MODEL AFTER DELETING RFM, KCV_19_5, KCV_19_2, KCV_19_3

DUE TO INSUFFICIENT FACTOR LOADINGS



APPENDIX L

STEPS OF MODEL MODIFICATION FOR MEASUREMENT MODEL

Step	FL < 0.5 (Deleted)	WEC (Correlate)	BEC (Deleted)	SRC (Deleted)
1	KCV_19_5 = 0.066			
	KCV_19_2 = 0.254			
	KCV_19_3 = 0.313			
	RFM = 0.169			
2		SYT1&2 = 42.464	RPS12	
		RFT3&5 = 35.864	RPS10	
		RFT1&2 = 27.484		
		SYT4&5 = 23.498		
		RPS5&6 = 21.384		
		SYT2&5 = 20.096		
3				