Optimizing COVID-19 Vaccine Strategies: An Advanced Hybrid Entropy Decision Model for Public Health Evaluation

by

Maryam Mozaffari

A Thesis submitted to the Faculty of Graduate and Postdoctoral Studies

of the University of Manitoba

in partial fulfilment of the requirements of the degree of

Master of Science

I. H. Asper School of Business, Department of Supply Chain

University of Manitoba

Winnipeg

Contents

List of Tables

List of Figures

Abstract

This study presents a hybrid-entropy-weighted modified TOPSIS framework for evaluating COVID-19 vaccines under differing epidemiological and logistical conditions. Using publicly available data for nine vaccines, eight criteria were examined: efficacy rate, side-effect severity, shelf life, number of doses, cross-protection, regulatory approval, age eligibility, and cost. Two objective weighting methods, Shannon entropy and Wen entropy, were applied. Shannon entropy assigned relatively higher weights to logistical and demographic criteria based on data dispersion, while Wen entropy produced a more even distribution across clinical and dosing-related criteria. Adjustable hybrid parameters (ϕ and λ) were incorporated to allow continuous shifts between emphasizing clinical performance and logistical considerations.

Sensitivity analysis indicated systematic ranking variations as ϕ changed. Sinopharm and Novavax frequently appeared among the top-ranked vaccines across multiple configurations. Pfizer-BioNTech and Moderna tended to rank higher in low-ϕ settings that assigned greater weight to efficacy and cross-protection. Sinovac tended to rank higher in high-ϕ settings that assigned greater weight to shelf life and safety. Scenario-specific recommendations were generated for three contexts: rural and low-resource rollouts, rapid outbreak response, and balanced national strategies.

This framework provides a clear structure for the assessment of vaccines through the combination of objective variability-based weighting systems with adjustable policy priorities, which allows a transparent, adaptable, and context-sensitive multi-criteria decision-making process in public health planning.

Contribution of Authors

This thesis is a single-authored work completed by **Maryam Mozaffari**. All parts of the research, including developing the research idea, designing the methodology, collecting and analyzing the data, interpreting the results, and writing the thesis were carried out by the author.

Dr. Srimantoorao S. Appadoo, the author's advisor, and **Dr. Yuvraj Gajpal**, the author's co-advisor, provided supervision, guidance on the methodology, and feedback throughout the research process. No other individuals were involved in carrying out the research or producing the results presented in this thesis.

Acknowledgement

First and foremost, I would like to express my deepest gratitude to my advisor, **Dr. Srimantoorao S. Appadoo**, for his continuous guidance, encouragement, and insightful feedback throughout the entire journey of this thesis. His expertise and mentorship have been instrumental in shaping the direction and quality of my research.

I am equally grateful to my co-advisor, **Dr. Yuvraj Gajpal**, whose thoughtful advice, academic rigor, and support have contributed significantly to the development and completion of this work. His perspectives and constructive critiques have deepened my understanding of the subject matter.

I would also like to sincerely thank my committee members, **Dr. Narendra Malalgoda** and **Dr. Michael Lukie**, for their valuable time, insightful comments, and helpful suggestions which have helped refine and strengthen my thesis.

Finally, I am deeply appreciative of the support, encouragement, and patience of my family, friends, and colleagues throughout this academic journey. Their belief in me has been a source of strength and motivation during the most challenging times.

Maryam Mozaffari

Chapter I: Introduction

1.1 Background and Context

The COVID-19 pandemic has changed the face of society all over the world. It put health systems to the test and called for quick, coordinated, and efficient public health actions to be taken in emergencies. This contagious disease is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which is a member of the Coronaviridae family that infects only humans and some other vertebrates (Gorbalenya et al., 2020). At the end of 2021, SARS-CoV-2 had caused more than 5.4 million deaths worldwide, and this number continued to increase in the following years (WHO, 2022). Figure 1 shows that, by the end of 2024, the overall count of confirmed COVID-19 deaths had exceeded 7 million, thus highlighting the continued severity and persistence of the crisis (Mathieu et al., n.d.).

Figure 1

Cumulative Confirmed COVID-19 Deaths by World Region. SOURCE: (Mathieu et al., n.d.)

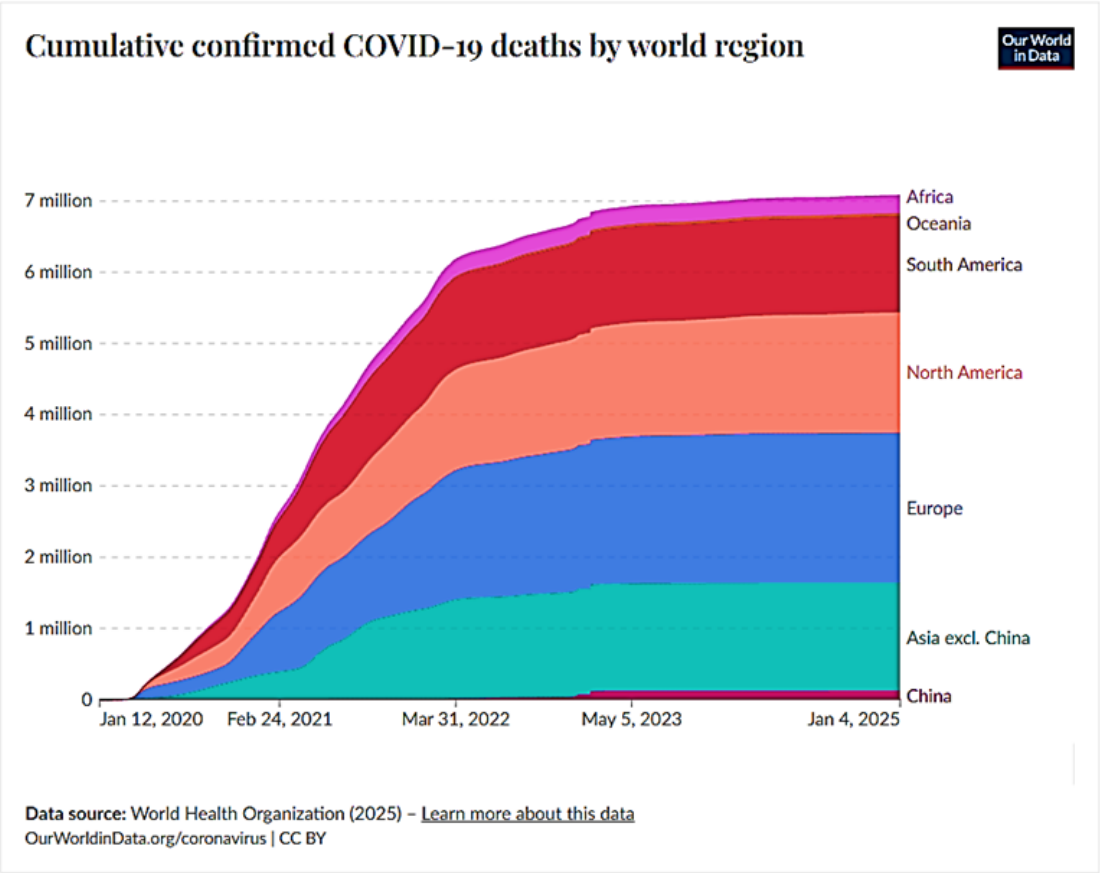


Figure 1 shows the significant global loss of life along with regional differences in death rates. The Americas and Europe have reported the highest numbers of deaths, while other regions have faced distinct challenges in managing the spread of the virus. These patterns highlight both the scale of the pandemic's impact and the complexity of the global public health response.

The pandemic also revealed persistent challenges of resource allocation in healthcare and a lack of preparedness for emergencies. Evidence from multiple countries suggested that even the best-equipped health systems faced difficulties in coping with the demands in this evolving crisis (Moradi et al., 2022). As the situation progressed, health systems faced increasing operating pressures, disruptions in supply chains, and major shifts in healthcare delivery (Antioch et al., 2024). Within this environment, the development, production, and distribution of vaccines became what

Arnold (2020, as cited in Mak et al., 2022, p. 2) referred to as the biggest logistics challenge in history, with billions of doses needing to be manufactured and delivered within a short time frame.

Public health officials faced multiple challenges, such as rapid spread of the virus and shortages of vaccines. They were required to design strategies that minimized mortality, the prevention of the healthcare system from collapsing, and reductions in social and economic disruptions. Decision-makers had to make rapid choices regarding which vaccines to procure and how to allocate limited doses among priority groups. These decisions involved complex ethical, logistical, and practical considerations (Almulhim & Barahona, 2022).

As vaccines were developed and deployed at unprecedented speed, additional scientific, logistical, and equity-related challenges emerged. A critical question that follows is how decision-makers would ensure that vaccine distribution remains both fair and effective under such uncertainty and complexity. The next section examines these challenges in more detail.

1.2 Problem Statement

The development of various COVID-19 vaccines was a critical point during the pandemic that offered a path toward controlling the virus and reducing its global impact. By November 2020, vaccine development had reached its fastest speed, supported by extensive partnerships among governments, international organizations, research institutions, and companies across the world (Fisher et al., 2021). However, many scholars emphasized that the scientific development of vaccines alone was not sufficient. Achieving widespread and equitable vaccination poses significantly greater challenges (Dai & Song, 2021).

Following vaccine development, countries faced a range of scientific, regulatory, and logistical challenges. Research teams and pharmaceutical manufacturers pursued different technological platforms, such as messenger Ribonucleic Acid (mRNA), viral vector, protein subunit, and inactivated virus vaccines (Tregoning et al., 2021). By the end of 2021, although hundreds of vaccine candidates had been under investigation, only a limited number received emergency approval, which increased the urgency and complexity of allocation decisions (King, 2024).

The introduction of two-dose vaccination created additional challenges for policymakers. They had to decide whether to reserve second doses for a smaller population to ensure complete protection ("hold-back" strategies), or to administer first doses to as many people as possible and accept the risk of later delays in second-dose availability ("stretching" strategies). Both strategies involved important trade-offs related to population immunity, long-term protection, feasibility, and fairness (Mak et al., 2022).

Logistical constraints further complicated vaccine distribution. Moving vaccines from manufacturing sites to communities worldwide included various activities such as raw material procurement, packaging, cold storage, and last-mile delivery. Shortages of glass vials and syringes, along with strict temperature requirements for certain vaccines, significantly increased the risks involved in the distribution process (Fisher et al., 2021). Experts warned that cold chain failures and logistical disruptions could cause substantial vaccine wastage. The World Health Organization (WHO) has estimated that up to 50% of vaccines globally become unusable each year due to improper temperature control and logistical issues (Wipperman, 2022).

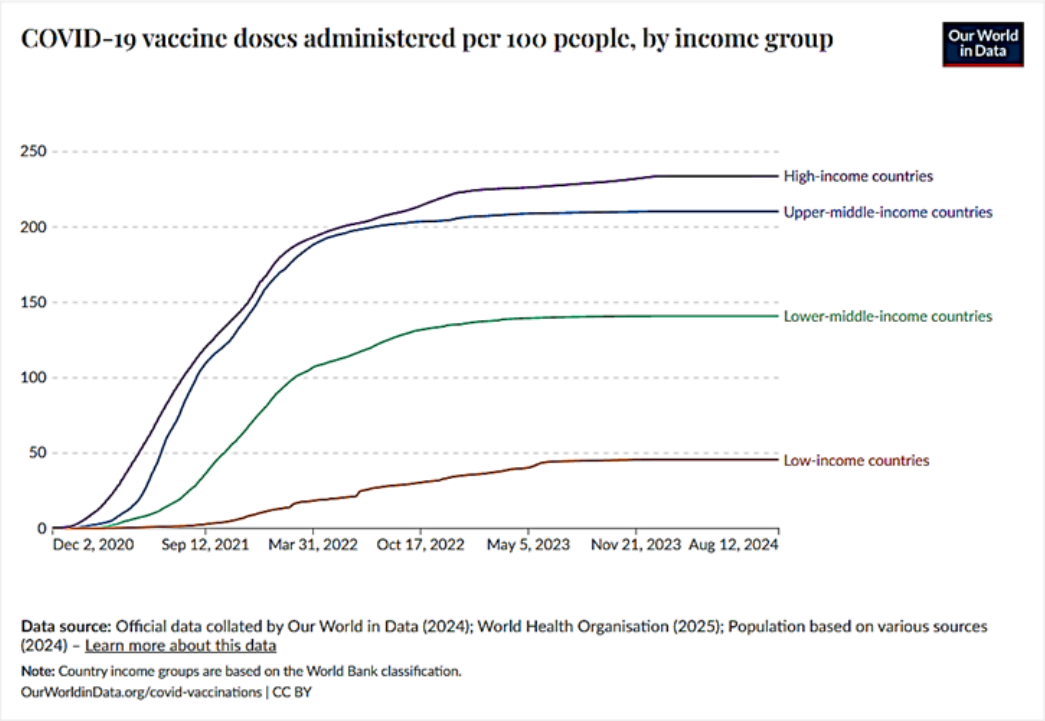
The severity of these challenges was clearly shown in India's second COVID-19 wave in April and May 2021, when daily infections exceeded 400,000 and health systems were overwhelmed (Puranam, 2021). Despite being one of the world's largest vaccine producers, India faced severe shortages due to procurement delays and export restrictions (Kidangoor, 2022). Another example is the destruction of nearly 20,000 expired vaccine doses in Malawi due to cold chain failures and delivery delays (Gondwe, 2021). These cases highlight weaknesses in vaccine supply chains and the need for decision-making tools that can incorporate logistical constraints and support fair allocation.

The global rollout also highlighted significant inequities. Early in the pandemic, high-income countries managed to secure a large amount of vaccine doses, which was often criticized as vaccine nationalism, while many low-income countries struggled to access enough supplies (Holleran et al., 2023).

These disparities are illustrated in Figure 2, which shows cumulative COVID-19 vaccine doses administered per 100 people, grouped by country income level (Mathieu et al., n.d.).

Figure 2

Cumulative COVID-19 Vaccine Distribution, by Income Group. SOURCE: (Mathieu et al., n.d.)



As shown in Figure 2, by mid-2022 high-income countries had administered more than 200 doses per 100 people, reflecting widespread full vaccination and the start of booster campaigns. In contrast, low-income countries administered fewer than 50 doses per 100 people even by 2024. Upper- and lower-middle-income countries fell between these extremes but did not reach the coverage levels of high-income countries. The huge gaps between these lines illustrate the global inequities that shaped vaccine distribution.

These inequities had tangible consequences. While high-income countries built substantial vaccine reserves, low-income countries remained vulnerable to outbreaks, new variants, and ongoing social and economic disruption. Efforts such as the COVID-19 Vaccines Global Access Facility (COVAX) tried to equalize vaccine access for different regions, but logistical problems, supply shortages, and political challenges limited their impacts (Fisher et al., 2021). Additionally, misinformation, conspiracy theories, and concerns about transparency reduced public trust in

vaccination. Research indicates that online rumours and conspiracy theories significantly contribute to vaccine hesitancy and mistrust (Islam et al., 2021).

Given these complexities, public health authorities required systematic and transparent evaluation tools. Therefore, vaccine selection became a multi-dimensional problem that required balancing clinical, logistical, economic, and social considerations (Forestal & Pi, 2022).

Several studies have emphasized that "selecting a vaccine for fighting a pandemic is one of the serious issues in healthcare" (Abdelwahab et al., 2021, p. 1). Yet only a limited number of mathematical models have been applied to support this process.

Each vaccine has a distinct profile: some offered high efficacy but required ultra-cold storage, while others were easier to distribute but were less effective against certain variants (Soheili et al., 2023). Policymakers had to evaluate multiple criteria, including efficacy, availability, side effects, and cost while dealing with uncertain and rapidly changing information (Forestal & Pi, 2022).

Although existing research covers vaccine development and distribution, a substantial gap remains in systematic frameworks for evaluating and ranking vaccines (Abdelwahab et al., 2021). In the early stages of the rollout, decision-making often took place under extreme time pressure with very little information available, and not through transparent and structured evaluation (Roy et al., 2022). As Abdelwahab et al. (2021) note, there is a lack of practical decision models that can incorporate all relevant criteria and adapt flexibly to new information or emerging vaccine alternatives.

Traditionally, public health agencies have relied on established methods for evaluating vaccine strategies. Economic methods such as cost-effectiveness analysis (CEA) and incremental cost-effectiveness ratios (ICER) have guided WHO resource allocation decisions for a long time by assessing costs relative to health benefits (Tan-Torres Edejer et al., 2003). Epidemiological modeling, especially dynamic models such as Susceptible-Exposed-Infectious-Recovered (SEIR), has helped organizations like the U.S. Centers for Disease Control and Prevention (CDC) and the Global Alliance for Vaccines and Immunization (Gavi) in forecasting the effects of different vaccination strategies (Joshi et al., 2021). Structured expert panels like Delphi processes and consensus

committees have also been instrumental in assessing uncertainties and improving recommendations for diverse contexts (Ariyarajah et al., 2022).

Although these methods offer valuable insights, they face limitations when it comes to the practical world. Many of these methods emphasized a single criterion such as cost or side effects reduction while overlooking the multi-dimensional trade-offs during vaccine deployment (Utami et al., 2022). Expert-based approaches also introduce subjectivity risks as they often lack transparent mechanisms to balance key considerations such as logistics, equity, and public trust (Sinuraya et al., 2024). These limitations show the need for more robust and adaptable decision-making tools, which this thesis aims to address.

Recognizing these constraints, this research proposes a hybrid-entropy-weighted modified TOPSIS model. Unlike traditional single-method or expert-based approaches, this model integrates the objectivity of Shannon entropy with the flexibility of Wen entropy. Through this combination, the study will address the real-world issues such as data uncertainty and non-linear relationships in vaccine selection. The following section outlines the objectives and research questions that guide this study.

1.3 Research Objectives and Questions

The vaccine selection process is complicated by nature and widely recognized as a multiple-criteria decision-making (MCDM) problem, as it requires balancing multiple conflicting and interrelated criteria (Abdelwahab et al., 2021). Policymakers have to consider the effectiveness and safety of vaccines along with cost, logistics, public acceptance, and suitability for different population groups (Soheili et al., 2023).

Recognizing these challenges, researchers have increasingly adopted MCDM frameworks, which are practical tools for supporting complex and time-sensitive decisions. These models are able to systematically incorporate both quantitative and qualitative factors, therefore improving consistency, transparency, and reliability in public health decision-making (Alsalem et al., 2022).

With the most acute phase of the pandemic now under better control and a wide range of

vaccines available, there is an opportunity to shift from reactive decision-making to more structured, data-driven approaches. Instead of single-criterion or ad hoc evaluations, policymakers will be able to apply systematic models that incorporate various forms of evidence and priorities (Williams et al., 2023).

Among the various MCDM methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is notable for its clarity, adaptability, and frequent use in healthcare applications. Its mechanism can comprehensively compare the strengths and weaknesses of each alternative (Hwang & Yoon, 1981).

However, the classical TOPSIS method has limitations. Its traditional structure relies on the subjective assignment of criteria weights, which may introduce bias and reduce transparency. Furthermore, healthcare data often involves uncertainty, non-linear relationships, and context-specific conditions that simple weighting schemes do not fully capture (Su & Sun, 2023).

Entropy-based weighting methods address these limitations by offering objective and data-driven criteria weights. Shannon entropy, introduced by Claude Shannon in 1948, measures the variability of each criterion within a dataset (Shannon, 1948). In vaccine evaluation, Shannon entropy highlights differences between criteria and assigns greater weight to those with higher information. Wen entropy, proposed by Wen, Chang, and You (1998), extends this approach by introducing a specialized mapping function that captures non-linearity and uncertainty. This mapping makes Wen entropy especially suitable for situations involving incomplete or imprecise data which are the common features in public health evaluation.

Although each entropy method has its own advantages, using them individually may limit their effectiveness. By combining these two methods, a hybrid approach effectively utilizes the precision and objectivity of Shannon entropy with the flexibility and robustness of Wen entropy. This dual method enhances the capability of MCDM models by accommodating both well-defined data and context-specific information (Appadoo et al., 2012).

Building on these considerations, this research proposes a hybrid-entropy-weighted modified TOPSIS model for systematic vaccine evaluation. This approach incorporates both objective and

flexible weighting to show the complexities of decision-maker priorities and the evolving nature of pandemic-related evidence. By integrating the strengths of both entropy techniques, the model provides a transparent, reproducible, and practical tool for ranking COVID-19 vaccines. To ensure accuracy and replicability, all calculations are implemented using Microsoft Excel and Python.

This thesis aims to develop, implement, and validate the hybrid-entropy-weighted modified TOPSIS model for vaccine evaluation. The specific objectives are:

1. To critically review and synthesize existing approaches to vaccine selection and multi-criteria decision-making in public health, identifying gaps, and opportunities for improvement.

2. To develop a hybrid entropy-based weighting scheme that integrates the strengths of both Shannon and Wen entropy for objective and flexible criteria weighting.

3. To adapt and extend the TOPSIS algorithm to improve its robustness and suitability for real-world vaccine evaluation.

4. To empirically validate the proposed model using publicly available vaccine data and conduct sensitivity analyses to assess its performance.

5. To provide evidence-based recommendations for policymakers, supply chain managers, and public health officials based on the study's findings.

Correspondingly, the thesis addresses the following research questions:

- How can a hybrid-entropy-weighted modified TOPSIS model improve transparency and effectiveness in COVID-19 vaccine selection?

- What are the comparative advantages and limitations of hybrid entropy weighting relative to single-method or subjective weighting approaches?

- How does the proposed model perform in practice, and what insights does it offer for future vaccine evaluation frameworks?

After establishing the research objectives and questions, we should consider the broader significance and potential contributions of this work to public health decision-making.

1.4 Significance and Contributions of the Study

This research contributes to the public health decision-making process in both the methodological and practical aspects. Methodologically, this research has developed a structured data-driven model that reflects the complexity of vaccine selection. The model, through the integration of hybrid entropy weighting with the TOPSIS framework, improves objectivity and flexibility, which helps policymakers to systematically evaluate criteria such as effectiveness, safety, logistics, cost, and equity.

Practically, the model offers a transparent and reproducible method for evaluating vaccines according to the evolving pandemic conditions. In addition, the framework, through integration of both clinical and logistical considerations, ensures that decisions are consistent, equitable, and informed, which in turn leads to better resource allocation and stronger preparedness for future health crises. The findings and recommendations of this research are applicable to decision-makers at institutional, national, and international levels helping to connect analytical methods with real-world public health practice.

1.5 Thesis Structure Overview

To guide the reader, the thesis is organized as follows:

Chapter 2: Literature Review: This chapter provides an overview of existing research on vaccine selection, with emphasis on MCDM frameworks and entropy-based weighting methods.

Chapter 3: Methodology: Chapter 3 presents the methodological framework developed for this study. It introduces the hybrid-entropy-weighted modified TOPSIS model and outlines the mathematical formulation.

Chapter 4: Data Collection: This chapter details the process of gathering and preparing the data used in the analysis. It describes the sources of COVID-19 vaccine data, the selection criteria, and

the construction of the decision matrix.

Chapter 5: Numerical Analysis and Results: In this chapter, the proposed hybrid-entropy-weighted modified TOPSIS model is applied to the collected data.

Chapter 6: Discussion: This chapter interprets the numerical results, comparing how Shannon, Wen, and hybrid entropy weights influence TOPSIS rankings and explains why certain vaccines remain consistent across values of ϕ and λ.

Chapter 7: Conclusion and Recommendations: The final chapter summarizes the empirical findings using Shannon, Wen, and hybrid weights, demonstrating how the parameters ϕ and λ support context-sensitive vaccine prioritization.

Chapter II: Literature Review

The COVID-19 pandemic has redefined the priorities of the public health sector and highlighted the weaknesses in health system preparedness, resource allocation, and scientific innovation (Kandulu et al., 2024). In this situation, the process of selecting the right vaccines became a complex task and highlighted the need for quick and evidence-based decisions that often involved ethical considerations. This section takes a closer look at the progress of the decision-making models for vaccine selection and allocation through time. It focuses particularly on the multi-criteria decision-making (MCDM) frameworks, the objective and hybrid weighting methods, and their empirical application throughout the COVID-19 pandemic.

2.1 Vaccine Selection in Pandemics

2.1.1 Global Vaccine Distribution: Achievements and Challenges

The selection and allocation of vaccines have always been pivotal factors in controlling infectious diseases, including smallpox, polio, and other illnesses. However, the COVID-19 pandemic intensified these challenges due to its global spread, the rapid emergence of new variants, and substantial constraints in production and distribution of vaccines (Duintjer Tebbens & Thompson, 2018; Kandulu et al., 2024).

Although the use of mathematical decision models for vaccine selection is still limited, earlier research provides valuable foundations. For instance, Höpping et al. (2016) analyzed influenza B vaccine lineage selection by examining the evolutionary dynamics of the virus. Their approach aimed to improve protection against both influenza B lineages while maintaining cost-effectiveness through the use of trivalent vaccines instead of quadrivalent options.

Evidence from international trials highlights the value of such structured decision strategies and shows that formal modeling can strengthen vaccination policy even outside the context of COVID-19.

2.1.2 Prioritization Frameworks in Public Health

During the initial phases of the COVID-19 vaccine rollout, prioritization frameworks were developed to maximize health benefits, promote fairness, and reduce disparities (Joshi et al., 2021). Organizations such as the U.S. Centers for Disease Control and Prevention (CDC), the World Health Organization (WHO), and the United Kingdom's Joint Committee on Vaccination and Immunization (JCVI) usually gave preference to high-risk groups like older adults, individuals with underlying conditions, and frontline workers. However, the standards for the classification of essential groups and the treatment of social vulnerability differed across national guidelines (Ferranna et al., 2021).

Mathematical and epidemiological models supported these frameworks by simulating alternative allocation strategies and assessing their effects on infection, hospitalization, and mortality (Hou & Bidkhori, 2024; Joshi et al., 2021). In many cases, the best strategy was determined by the dominant policy objective (e.g., death vs. infection minimization), the epidemiological situation, and the characteristics of the available vaccines.

While prioritization frameworks are valuable for identifying key groups and supporting ethical allocations, they rely on traditional methodological approaches. Therefore, the next section examines traditional decision-making methods and outlines their advantages and limitations.

2.2 Traditional Decision Frameworks

Traditional methods have influenced public health policy and vaccine allocation for a long time. They have been the main basis for interventions prioritization, including financial analysis, epidemiological predictions, and expert opinions. The following subsections outline several commonly used traditional frameworks.

Cost-Effectiveness Analysis (CEA) and Incremental Cost-Effectiveness Ratios (ICER)

Cost-effectiveness analysis, and the incremental cost-effectiveness ratio, are widely used for allocating health resources, particularly in low- and middle-income countries with constrained budgets (Utami et al., 2022; Tan-Torres Edejer et al., 2003). CEA evaluates the costs and health benefits of different interventions in order to enable the efficient use of resources. Key measures for these methods include the Quality-Adjusted Life Year (QALY), representing one year of life in perfect health, and the Disability-Adjusted Life Year (DALY), indicating the loss of one year of healthy life due to illness, disability, or premature death. Southern Africa, Pakistan, Turkey, and Thailand have provided compelling evidence, through their respective studies, which indicates that COVID-19 vaccination strategies are highly cost-effective or even cost-saving (Utami et al., 2022).

Despite its usefulness, CEA has limitations. It mainly focuses on costs and health outcomes, but often does not consider broader aspects such as equity, social vulnerability, and logistical feasibility. As a result, important societal and operational dimensions may be overlooked. CEA is also context-specific: findings depend heavily on local epidemiology, resources, and demographics, which limit the generalizability of results to other settings. Furthermore, the method is still unable to capture the evolving trade-offs faced during public health emergencies, when ethical, social, and practical priorities can change instantly (Tan-Torres Edejer et al., 2003; Blasioli et al., 2023).

Epidemiological Modeling

Compartmental models such as Susceptible-Exposed-Infectious-Recovered (SEIR) and Susceptible-Infectious-Recovered (SIR) are the most common methods for predicting the spread of infection and for assessing the distribution of vaccines (Hou & Bidkhori, 2024).

For example, the SEIR model categorizes the population as follows (Al-Jebouri et al., 2025):

- **Susceptible (S):** Individuals who can contract the disease.
- **Exposed (E):** Individuals who have been infected but are not yet infectious.
- **Infectious (I):** Individuals who can transmit the disease to others.

- **Recovered (R):** Individuals who have recovered and are assumed to have immunity.

The model tracks transitions between these groups to understand and predict outbreak dynamics.

While epidemiological models provide valuable insights for forecasting and planning, they still have constraints. Traditional models often consider the population to be homogeneous, which results in overlooking differences in risk, exposure, and behavior among the groups. They may also struggle to consider logistical constraints, rare events, and the influence of individual or collective behavior on transmission. Consequently, relying exclusively on epidemiological models may not fully reflect the complexities of a real-world pandemic response. Recently, there is recognition that these models should be integrated with economic, logistical, and equity considerations to support more comprehensive public health decisions (Duintjer Tebbens & Thompson, 2018).

Although traditional approaches remain important, their narrow focus and underlying assumptions limit their effectiveness in complex decision environments. This has contributed to growing interest in multi-criteria decision-making methods, which are introduced in the following section.

2.3 Multi-Criteria Decision-Making: Methods, Applications, and Advances

Multi-criteria decision-making (MCDM) methods have the ability to address the limitations of single-objective frameworks by considering multiple, often conflicting, criteria in the process of alternatives evaluation (Alamoodi et al., 2023; Sotoudeh-Anvari, 2022). Over the past decade, a range of MCDM techniques has been applied to health-related decision-making, including vaccine selection during the COVID-19 pandemic. Commonly used MCDM methods include the following:

- ✦ **AHP (Analytic Hierarchy Process):** AHP is a subjective decision-making method developed by Thomas Saaty in 1980. It enhances prioritization by breaking down a complex problem into a hierarchy, using pairwise comparisons to distribute numerical weights, and generating a ranking of alternatives (Saaty, 2008).

- ✦ **TOPSIS (Technique for Order Preference by Similarity to Ideal Solution):** Developed by Hwang and Yoon in 1981, TOPSIS ranks alternatives based on their geometric distances to an ideal solution and a negative-ideal solution. The preferred alternative is the one closest to the ideal and farthest from the negative-ideal (Appadoo et al., 2012). TOPSIS is mostly famous for its transparency, ease of implementation, and compatibility with software tools such as Excel or Python. It allows the use of both benefit and cost criteria along with externally derived weights, which makes it suitable for adaptive weighting strategies in this thesis (Forestal et al., 2021).

- ✦ **VIKOR ("Multi-criteria Optimization and Compromise Solution Ranking"):** Introduced by Opricovic in 1998, VIKOR focuses on ranking and selecting alternatives under conflicting criteria by seeking a compromise solution (Opricovic & Tzeng, 2004).

- ✦ **PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations):** Proposed by Brans and colleagues in the 1980s, this method uses preference functions to perform pairwise comparisons between alternatives and provides complete or partial rankings (Brans & Vincke, 1985).

- ✦ **ELECTRE (Elimination and Choice Expressing Reality):** Developed by Bernard Roy in the 1960s, ELECTRE uses outranking relations to evaluate and eliminate alternatives in the presence of conflicting criteria (Roy, 1991).

Having outlined core MCDM methods, the following reviews their applications in COVID-19 vaccine selection and prioritization.

Recent empirical work indicates how researchers adapted these models for pandemic-related decisions. For example, Abdelwahab et al. (2021) applied AHP to rank six COVID-19 vaccines using expert assessments. Their study demonstrated the usefulness of AHP in structuring decision-making but also highlighted challenges related to maintaining consistency in subjective judgments.

To address the limitations of single-method approaches, Forestal et al. (2021) proposed a hybrid model that combined ELECTRE III for concordance analysis, genetic algorithms for preference

disaggregation, and TOPSIS for final ranking. Their results emphasized the importance of safety, efficacy, and availability.

In a different case, Üner et al. (2023) developed an integrated AHP–PROMETHEE framework to prioritize individuals for vaccination when supply was limited. AHP was used to determine the weights of criteria such as age, comorbidities, and occupational exposure, while PROMETHEE generated the final ranking.

Mallick et al. (2024) provided an extension of VIKOR to COVID-19 vaccine selection by creating a quadripartition neutrosophic number (QNN)-based hybrid method, which integrated both TOPSIS and VIKOR. Their approach applied an entropy-based weighting system to evaluate criteria such as safety, efficacy, availability, and cost. However, the complexity of neutrosophic logic and hybrid modeling can pose challenges for interpretation and practical implementation in policy settings.

Beyond direct vaccine selection, MCDM methods have been applied to broader healthcare decision-making:

- **Supply Chain and Logistics:** MCDM methods have been integrated into healthcare supply chain and logistics models to support decisions under uncertain conditions. Chen (2021) applied an entropy-weighted TOPSIS model for the selection of suppliers and optimization of logistics. Dey et al. (2023) reviewed the management of vaccine supply chains and pointed out that MCDM methods, especially AHP and TOPSIS, often support broader optimization frameworks for distribution planning, risk assessment, and resource allocation.

- **Hospital and ICU Allocation:** MCDM methods have played a crucial role in supporting resource allocation in hospitals and intensive care units during the pandemic (Yang et al., 2022). Alamoodi et al. (2023) reviewed applications of AHP, TOPSIS, VIKOR, PROMETHEE, and ELECTRE in decision problems such as hospital selection, ICU prioritization, and capacity planning. These methods help improve transparency and reproducibility in limited resource settings. Blasioli et al. (2023) also highlighted the importance of multi-criteria approaches for evaluating policy trade-offs.

- **Public Health Interventions:** MCDM methods have been applied to decisions involving masks, hand sanitizers, and other non-pharmaceutical interventions. AHP and TOPSIS have been employed for evaluating alternatives based on criteria such as effectiveness, cost, comfort, and accessibility, using both expert judgment and quantitative evidence (Sotoudeh-Anvari, 2022).

The diversity of vaccine characteristics, combined with evolving scientific knowledge, public opinions, and global supply constraints, created a situation that needs systematic, transparent, and adaptable decision-making frameworks (Alamoodi et al., 2023). As the effectiveness of these frameworks is closely tied to the criteria weighting, the next section examines weighting approaches, including subjective, objective, and hybrid strategies.

2.4 Criteria Weighting in MCDM

The assignment of weights to criteria for evaluation is a step that plays a critical role in MCDM. The ranking of alternatives is influenced by the weight of each criterion. For producing reliable and meaningful decision outcomes, the accuracy and appropriateness of these weights are essential (Singh & Pant, 2021).

2.4.1 Subjective vs. Objective Weighting

Weighting methods in the literature are commonly grouped into two categories: subjective and objective approaches. Each category has its own strengths and limitations, and the choice of method can affect the outcomes of any MCDM application.

Subjective Weighting: Subjective weighting relies on the judgments, experience, and preferences of decision-makers or experts to determine the importance of each criterion. Methods such as the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) are among the most frequently used techniques for this purpose that allow qualitative insights and expert perspectives to be incorporated into the weighting process (Saaty, 2008; Chen, 2021).

Although decision-makers can apply subjective weighting to indicate contextual needs and stakeholder priorities, it is also susceptible to bias, inconsistency, and variability, especially when expert opinions diverge or consensus is difficult to achieve. Expert judgments may be influenced by personal preferences, organizational norms, or recent experiences, which can distort the weighting outcomes (Kizielewicz et al., 2024). As the number of criteria increases, subjective methods such as AHP and ANP require numerous pairwise comparisons, increasing the likelihood of inconsistencies. While consistency indices help identify variations, they cannot fully correct them, and high inconsistency may affect the validity of the resulting weights (Saaty & Tran, 2007).

Group decision-making processes may also introduce challenges. Reaching an agreement can be time-intensive, and outcomes may reflect dominant viewpoints rather than collective judgment (Saaty, 2008). Subjective weighting is typically less transparent than objective methods because results depend heavily on the selected experts, their training, and their backgrounds. This lack of transparency makes replication difficult and reduces external validation (Ponhan & Sureeyatanapas, 2022). Additionally, subjective weights are often context-specific and may not be generalized across different settings or populations.

Objective Weighting: Objective weighting methods determine the weights of criteria through the statistical characteristics of the decision matrix so they do not depend on expert opinions directly. Common objective techniques include entropy-based weighting (Shannon and Wen), standard deviation, and the Criteria Importance Through Intercriteria Correlation (CRITIC) method (Singh & Pant, 2021).

Objective approaches offer several advantages. They minimize the influence of personal bias as the data characteristics alone determine the weights (Ponhan & Sureeyatanapas, 2022). This objectivity ensures that criteria with greater variability or information content receive higher weights, independent of subjective judgment. These methods are also transparent and reproducible, as they rely on explicit mathematical formulas that can be independently verified (Shannon, 1948; Wen et al., 1998). Furthermore, objective methods are applicable to large-scale problems that consist of numerous criteria or alternatives, where subjective techniques may become impractical in the same

situation (Ponhan & Sureeyatanapas, 2022).

2.4.2 Hybrid Weighting Approaches

A growing number of studies support hybrid weighting approaches, particularly those that combine subjective methods (such as AHP or ANP) with objective approaches (such as entropy weighting). These hybrid models often provide improved accuracy, stability, and robustness compared to using a single method (Chen, 2021). However, most existing hybrid frameworks focus on integrating subjective and objective weights and have not considered to combine multiple objective weighting methods within the same MCDM framework.

The possibility of combining various entropy-based weighting techniques, like Shannon entropy and Wen entropy, and analyzing the impact of their proportions on the ranking results still has not been thoroughly investigated. This gap is especially evident in the healthcare domain where uncertainties in data, non-linear relationships, and context-specific dynamics are common.

In order to address this gap, this research introduces a flexible, proportion-based integration of Shannon and Wen entropy weights within the TOPSIS method. This approach offers a more adaptable and robust weighting structure for vaccine selection, thus facilitating the theoretical development and practical application of objective MCDM techniques in public health decision-making.

2.5 Challenges and Research Gaps

Despite the fact that MCDM methods have made considerable progress in areas like engineering and logistics, their application in healthcare, especially in the case of vaccine selection, is still relatively limited (Alamoodi et al., 2023; Sotoudeh-Anvari, 2022). Recent systematic reviews indicate that only a small fraction of healthcare decision models incorporate advanced MCDM techniques and it appears that among the few that do, the majority are still primarily using subjective weighting methods (Abdelwahab et al., 2021). The heavy dependence on expert judgment and subjective frameworks such as AHP and ANP reflects a reliance on specialized expertise and highlights the

lack of practical, data-driven alternatives that have been validated in real-world settings.

In the case of TOPSIS, most healthcare applications use subjective weighting methods (Chen, 2021). According to the studies, fully objective or hybrid objective weighting strategies, including combinations of Shannon and Wen entropy, have been almost non-existent. The literature often does not explore the advantages of integrating multiple objective weighting methods or adjusting their relative influence to improve ranking stability, transparency, and robustness. Systematic reviews such as those by SotoudehAnvari (2022) and Alamoodi et al. (2023) emphasize that although hybrid approaches are gaining attention conceptually, few empirical studies in healthcare fully utilize the complementary strengths of different entropy-based weights.

These gaps have important implications for health policy. If the weighting approaches are not rigorous, flexible, and transparent, the process of decision-making may become less data-driven and more biased. A review of the literature highlights the need for methods that are both robust and practical enough to be relied on and used by decision-makers (Alamoodi et al., 2023).

However, the computational complexity and limited interpretability of many hybrid models are among the additional challenges. Although these approaches may have theoretical advantages, they often do not provide clear guidance for public health practitioners. Moreover, most studies do not offer visual aids or user-friendly tools, which makes it even less probable that their models will be adopted in actual policy settings (Sotoudeh-Anvari, 2022; Duintjer Tebbens & Thompson, 2018).

To address the methodological gaps identified in the literature, this research proposes a hybrid-entropy-weighted modified TOPSIS model, which is capable of enhancing rigor, adaptability, and transparency in vaccine selection. The approach combines the objectivity of Shannon entropy with the flexibility of Wen entropy allows for proportional adjustment of their weights in the TOPSIS framework. This integration improves ranking stability, interpretability, and practical relevance, directly responding to limitations in existing healthcare decision models. The key advantages of the proposed model include:

- ✓ **Objectivity and Rigor:** Introduces a data-driven weighting structure that reduces reliance on subjective assessments.

- ✓ **Flexibility and Robustness:** Examines how varying the proportion of different entropy-based weights influences ranking stability and model transparency.
- ✓ **Scenario-specific Adaptability:** Supports decision-making across diverse epidemiological and logistical contexts, which is essential during rapidly evolving public health emergencies.
- ✓ **Bridging Theory and Practice:** Provides an empirically tested model that is interpretable, adaptable, and suitable for integration into policy-oriented decision-support systems.

Therefore, the model is both analytically rigorous and practically applicable. By improving transparency and communication, the model enables public health practitioners and policymakers to understand the results and adjust decisions as the situation changes. This level of accessibility is critical for the successful implementation of advanced MCDM models in real-world health policy settings.

2.6 Summary Table

The key methods are summarized in Table 1 which outlines their primary strengths and limitations.

Table 1

Summary of Key Methods, Strengths, Limitations, and Applications

Method / Model	Core Strengths	Main Limitations	Applications	Key References
CEA / ICER	Widely used; focuses on efficiency and cost; standardized metrics	Narrow focus (cost, health); overlooks equity, logistics, evolving priorities	Economic evaluation; public health policy	Tan-Torres Edejer et al., 2003; Utami et al., 2022
Epidemiological Modeling	Simulates disease dynamics; supports prioritization; quantifies impact	Assumes homogeneity; lacks logistics/social context; complex for rare events	Allocation scenarios; resource planning	Duintjer Tebbens & Thompson, 2018; Hou & Bidkhori, 2024
AHP	Captures expert insight; intuitive pairwise comparisons; widely accepted	Subjective bias; inconsistency; context-specific weights	Vaccine selection; hospital/ICU resource allocation	Abdelwahab et al., 2021; Sotoudeh-Anvari, 2022
TOPSIS	Data-driven; clear ranking; adapts to multiple criteria	Sensitive to weights; data quality crucial	Vaccine/supplier selection; logistics; clinical decisions	Hwang & Yoon, 1981; Forestal et al., 2021; Chen, 2021
VIKOR	Handles conflicting criteria; provides compromise solutions	Complexity; requires precise definition of group utility/strategy	Vaccine selection; hospital ranking	Mallick et al., 2024; Opricovic & Tzeng, 2004
PROMETHEE	Flexible preference functions; handles many criteria; clear outranking	Needs subjective preference parameters; interpretation can be complex	Vaccine allocation; public health prioritization	Brans & Vincke, 1985; Üner et al., 2023; Alamoodi et al., 2023
ELECTRE / ELECTRE III	Good for eliminating non-viable options; deals with discordance	Threshold setting; can be complex to interpret	Hybrid models for vaccine selection	Roy, 1991; Forestal et al., 2021; Sotoudeh-Anvari, 2022
Objective Weighting (Entropy, CRITIC, SD)	Data-driven, replicable, less bias; scalable	May ignore context; dependent on input data quality	Weight assignment for MCDM models	Shannon, 1948; Wen, Chang & You, 1998; Chen, 2021
Hybrid Weighting (Subjective + Objective)	Greater robustness and accuracy; combines strengths of both approaches	Most focus on subjective-objective combos; little on combining multiple objective methods	MCDM for health; adaptive policy models	Chen, 2021; Appadoo et al., 2012; Singh & Pant, 2021
Hybrid MCDM Models	Highly flexible, adaptive, robust to uncertainty; can integrate multiple logics	Can be computationally complex, less interpretable	Complex vaccine/resource selection problems	Alsalem et al., 2022

Chapter III: Methodology

The COVID-19 pandemic, emergence of new variants, and disruptions in global supply chains have highlighted the need for decision-making tools that are transparent, data-driven, and capable of incorporating multiple, often conflicting, criteria. In this context, MCDM models have become important frameworks for offering systematic and reproducible assessments of alternatives in real-world settings (Alamoodi et al., 2023; Forestal et al., 2021).

However, putting these models into practice poses challenges. Traditional approaches such as cost-effectiveness analysis and epidemiological modeling are valuable, but they often address only specific aspects of decision-making and may overlook important factors related to logistics, equity, or public trust (Utami et al., 2022; Tan-Torres Edejer et al., 2003). In addition, many MCDM applications in healthcare have historically relied on subjective weighting methods, which can introduce bias and limit transparency and reproducibility (Abdelwahab et al., 2021; Ponhan & Sureeyatanapas, 2022).

This thesis addresses these gaps in COVID-19 vaccine evaluation by introducing a hybrid-entropy-weighted modified TOPSIS model. Building on recent developments in MCDM theory and applications, the framework provides an objective, flexible, and rigorous approach to ranking vaccines across clinical, logistical, and societal criteria.

3.1 Research Design and Framework

In this thesis, the research design is a quantitative, model-based study aimed at the development, implementation, and empirical validation of a multi-criteria decision-making framework for the selection of COVID-19 vaccines. This approach integrates established practices from decision sciences, public health analytics, and operations research to ensure methodological rigor.

The first step involves defining the decision criteria and vaccine alternatives. Following this step, data are collected from authoritative sources, including peer-reviewed literature, national and international health agencies (e.g., WHO, CDC), and official documents from manufacturers.

Chapter 4 provides a detailed description of data collection procedures, verification steps, and construction of the decision matrix.

After establishing the decision matrix, criterion weights are calculated using a hybrid entropy method. Shannon entropy captures variability in the data, while Wen entropy accounts for non-linearity and contextual uncertainty (Shannon, 1948; Wen et al., 1998). Together, they generate objective and adaptable weights for each criterion. Once the weights are determined, the TOPSIS method is applied to evaluate and rank the vaccine alternatives.

The analysis also includes scenario testing through systematic variation of the entropy parameters. By observing how rankings shift when weights change, the study assesses the reliability of the results and identifies which criteria and vaccines are most sensitive to uncertainty. These insights support practical recommendations for policymakers and public health decision-makers.

The next section presents a detailed explanation of the TOPSIS methodology, its mathematical formulation, and its role in complex public health decision-making, such as COVID-19 vaccine selection.

3.2 TOPSIS Methodology

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which was developed by Hwang and Yoon in 1981, is a widely used MCDM method that, through assessing the performance of different alternatives concerning several criteria, finds the one that is most preferred. As noted by Triantaphyllou (2000), the core idea of TOPSIS is to select the alternative that is closest to the ideal solution and farthest from the negative-ideal solution.

In healthcare and public health applications, TOPSIS has gained attention due to its clarity, computational efficiency, and ability to incorporate diverse quantitative and qualitative criteria. During the COVID-19 pandemic, researchers applied TOPSIS to support decisions related to vaccine evaluation, medical resource prioritization, and hospital performance assessment (Forestal et al., 2021; Chen, 2021).

Consider an MCDM problem with m alternatives, $A_1, \ldots, A_m$, and n criteria, $C_1, \ldots, C_n$. The

evaluations of the alternatives form a decision matrix D:

$$\mathbf{D} = [x_{ij}] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{3.1}$$

The weight vector $\mathbf{w} = (w_1, \ldots, w_n)$ represents the relative importance of the criteria and satisfies $\sum_{j=1}^{n} w_j = 1$.

The TOPSIS procedure consists of the following steps, based on Hwang and Yoon (1981), Triantaphyllou (2000), and Yoon and Hwang (1995):

STEP 1: Normalization of the Decision Matrix

The normalized value r_{ij} is computed as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1, 2, \ldots, m, \; j = 1, 2, \ldots, n \tag{3.2}$$

This converts all criteria to a dimensionless scale, preventing any criterion from dominating due to differences in units or magnitude.

STEP 2: Construction of the Weighted Normalized Decision Matrix

Weights obtained from the hybrid entropy method (combining Shannon and Wen entropy) are applied to the normalized matrix:

$$V = (w_j r_{ij})_{m \times n} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix}. \tag{3.3}$$

STEP 3: Identification of Ideal and Negative-Ideal Solutions

The ideal and negative-ideal solutions are defined as:

$$A^+ = \{\max_i v_{ij} \mid j \in \Omega_b; \min_i v_{ij} \mid j \in \Omega_c\} = (v_1^+, \ldots, v_n^+) \tag{3.4}$$

$$A^- = \{\min_i v_{ij} \mid j \in \Omega_b; \max_i v_{ij} \mid j \in \Omega_c\} = (v_1^-, \ldots, v_n^-) \tag{3.5}$$

Where Ω_b and Ω_c denote benefit and cost criteria, respectively.

STEP 4: Computation of Separation Measures

The Euclidean distances of each alternative from the ideal and negative-ideal solutions are:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \tag{3.6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \tag{3.7}$$

STEP 5: Calculation of Relative Closeness to the Ideal Solution

The relative closeness coefficient is:

$$RC_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{3.8}$$

A larger RC_i indicates better performance.

STEP 6: Ranking the Alternatives

Finally, alternatives are ranked in descending order of RC_i, with the highest value representing the most preferred option.

TOPSIS offers several advantages that support its widespread use in MCDM applications. The ranking process is very clear and interpretable as it is based on the closeness of the solutions

to both ideal and negative-ideal solutions (Hwang & Yoon, 1981; Triantaphyllou, 2000). The method is capable of taking a large number of alternatives and criteria into account so that it can be applied to complex problems in areas like healthcare, environmental management, and supply chain analysis (Behzadian et al., 2012; Forestal et al., 2021). Its adaptable formula makes it possible to combine both qualitative and quantitative criteria and to use different weighting methods, which adds to the flexibility of the application (Opricovic & Tzeng, 2004). Additionally, TOPSIS does not require independence among criteria or strict preference structures, which increases its usefulness in uncertain or dynamic contexts (Ciardiello et al., 2023).

As previously mentioned, TOPSIS rankings are sensitive to the choice of criterion weights. To address this issue, the current study employs a hybrid entropy-based weighting approach. The next section explains the development and application of this weighting scheme.

3.3 Weighting Scheme

The reliability of any MCDM method depends strongly on how criterion weights are determined (Singh & Pant, 2021). Traditional weighting methods in TOPSIS often rely on subjective opinions of experts, which can lead to bias and reduce transparency (Kizielewicz et al., 2024). To strengthen objectivity and consistency, this study adopts a hybrid entropy weighting scheme. By combining Shannon entropy and Wen entropy, the approach captures both information variability and contextual uncertainty in the data.

3.3.1 Shannon Entropy Weighting

Shannon entropy was originally introduced in the context of information theory (Shannon, 1948) and is widely applied in MCDM as an objective method for deriving criterion weights. The core concept is that those criteria, which show a greater variability across alternatives contain more information and therefore are assigned higher weights. On the other hand, criteria with similar values across alternatives contribute less information and receive lower weights (Wu et al., 2011).

Let the decision matrix D of m alternatives and n criteria be:

$$\mathbf{D} = [x_{ij}] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{3.9}$$

The Shannon entropy weighting procedure consists of the following steps (Hwang & Yoon, 1981; Zou et al., 2006):

STEP 1: Normalization of the Decision Matrix

The normalized value r_{ij} for each entry is calculated as:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \quad i = 1, \ldots, m; \; j = 1, \ldots, n \tag{3.10}$$

This normalization process transforms all entries into values between 0 and 1, ensuring that the sum of all normalized values across alternatives equals one for each criterion.

STEP 2: Calculation of Entropy

The entropy E_j for criterion j is defined as:

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}, \quad j = 1, \ldots, n \tag{3.11}$$

The constant $\frac{1}{\ln m}$ ensures $0 \leq E_j \leq 1$. When $r_{ij} = 0$, the expression $r_{ij} \ln r_{ij}$ is defined as zero.

STEP 3: Calculation of the Degree of Diversification

The degree of diversification for each criterion is then determined by:

$$d_j = 1 - E_j \tag{3.12}$$

A larger d_j indicates greater variability and provides more valuable information.

STEP 4: Calculation of the Entropy Weight

Finally, the entropy weight for each criterion is calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{3.13}$$

Alternatively,

$$w_j = \frac{1 + \frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}}{n + \sum_{j=1}^{n} \left(\frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij} \right)}. \tag{3.14}$$

This entropy weight describes the relative importance of each criterion.

Shannon entropy offers several advantages. It is a fully data-driven approach that reduces subjective influence and enhances transparency by relying on clearly defined mathematical relationships (Wu et al., 2022). In addition, it highlights criteria with greater discriminative ability and assigns them higher weights (Wu et al., 2011). The method is reproducible and suitable for situations where expert input is limited or where objective assessment is necessary (Ponhan & Sureeyatanapas, 2022).

However, Shannon entropy has limitations. In situations where the variability of criteria is limited, this method often assigns low weights to all the criteria, even if in reality some criteria are more important (Wu et al., 2022). It is also sensitive to outliers, which may cause the distortion of

the weights and the reduction of robustness (Zhu et al., 2020). Moreover, it does not account for non-linear or context-dependent uncertainties.

To address these limitations, the next section introduces the Wen entropy method, which extends entropy weighting to incorporate non-linear relationships and greater data complexity.

3.3.2 Wen Entropy Weighting

While Shannon entropy derives criterion weights based on information variability, the Wen entropy method, introduced by Wen et al. (1998), extends the entropy concept through a non-linear formulation that allows a more flexible assessment of uncertainty in decision matrices. This method, which draws on principles from gray system theory, is useful for problems involving incomplete, imprecise, or heterogeneous data because it captures both linear and non-linear characteristics within the data (Wen et al., 1998).

Wen entropy uses a non-linear mapping function $w_e(x)$ that satisfies the following conditions (Wen et al., 1998; Chiang & Hsieh, 2009; Hsu, 2013; Jangra et al., 2016):

- $f_i(0) = 0$
- $f_i(x) = f_i(1 - x)$ (symmetry)
- $f_i(x)$ is monotonic increasing for $x \in (0, 0.5)$

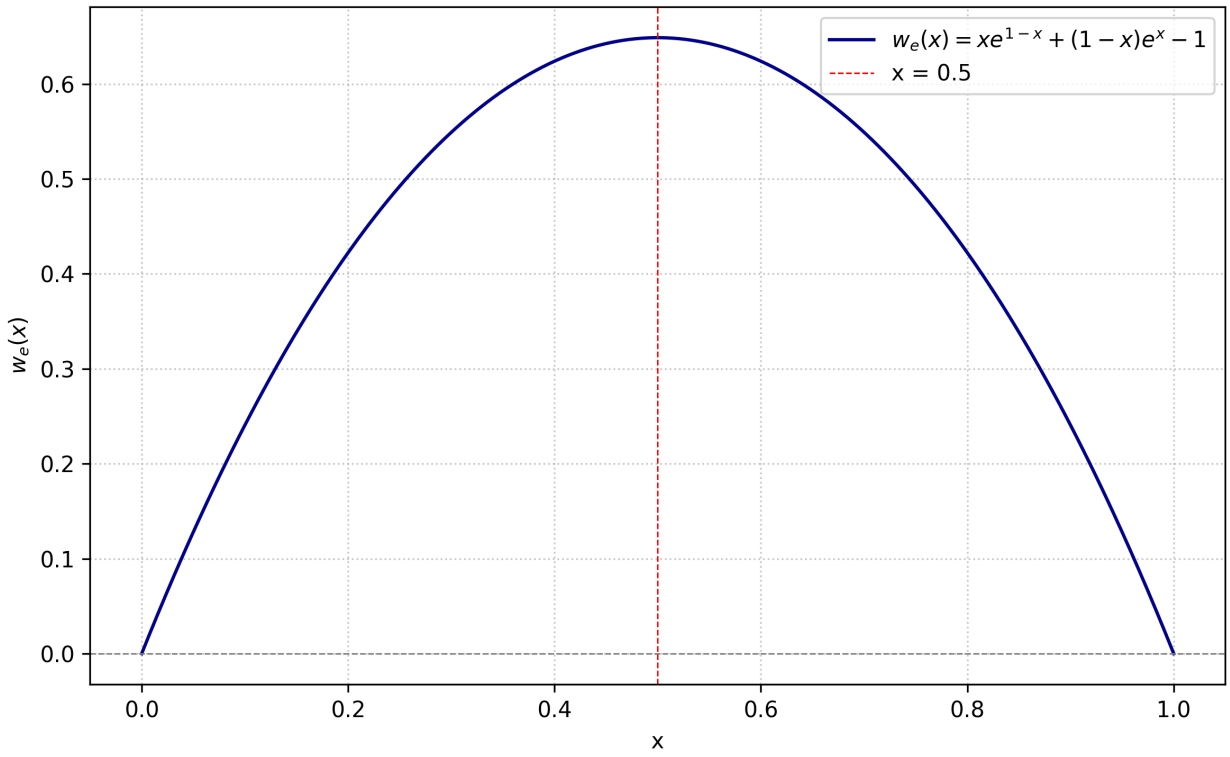
A function that satisfies these properties is:

$$w_e(x) = xe^{1-x} + (1 - x)e^x - 1 \tag{3.15}$$

This function reaches its maximum at $x = 0.5$, with a value of $e^{0.5} - 1 \approx 0.6487$ (Figure 3).

Figure 3

Wen Entropy Mapping Function



The Wen entropy weighting procedure consists of the following steps:

STEP 1: Normalization of the Decision Matrix

For the decision matrix $D = [x_{ij}]_{m\times n}$, normalized values are computed as (Li et al., 2011):

$$r_{ij} = \begin{cases} \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, & \text{if } j \text{ is a benefit criterion} \\ \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, & \text{if } j \text{ is a cost criterion} \end{cases} \tag{3.16}$$

This ensures that all r_{ij} values remain within $[0, 1]$.

STEP 2: Computation of the Sum for Each Criterion

$$D_j = \sum_{i=1}^{m} r_{ij}, \quad j = 1, \ldots, n \tag{3.17}$$

STEP 3: Calculation of the Normalized Coefficient

$$K = \frac{1}{(e^{0.5} - 1)m} \approx \frac{1}{0.6487m} \tag{3.18}$$

K ensures that the entropy values are correctly normalized based on the number of alternatives m.

STEP 4: Calculation of Wen Entropy for Each Criterion

Using Equation 3.15, Wen entropy for criterion j is:

$$e_j = K \sum_{i=1}^{m} w_e \left(\frac{r_{ij}}{D_j} \right) \tag{3.19}$$

More explicitly,

$$e_j = \frac{1}{0.6487\, m} \sum_{i=1}^{m} \left[\frac{r_{ij}}{D_j} e^{\left(1 - \frac{r_{ij}}{D_j}\right)} + \left(1 - \frac{r_{ij}}{D_j}\right) e^{\frac{r_{ij}}{D_j}} - 1 \right]$$

STEP 5: Calculation of Total Entropy

Total entropy E is calculated as:

$$E = \sum_{j=1}^{n} e_j = \sum_{j=1}^{n} \left(\frac{1}{0.6487\, m} \sum_{i=1}^{m} \left[\frac{r_{ij}}{D_j} e^{\left(1 - \frac{r_{ij}}{D_j}\right)} + \left(1 - \frac{r_{ij}}{D_j}\right) e^{\frac{r_{ij}}{D_j}} - 1 \right] \right) \tag{3.20}$$
$$\forall\ i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n$$

STEP 6: Calculation of Wen Entropy Weights

Finally Wen entropy is defined as:

$$w_j = \frac{1 - e_j}{n - E} = \frac{\frac{1}{n-E}[1 - e_j]}{\sum_{j=1}^{n} \frac{1}{n - E}[1 - e_j]}, \quad \forall\, j = 1, 2, \ldots, n \tag{3.21}$$

This step produces the normalized entropy weight for each criterion.

Wen entropy offers several advantages. The non-linearity of its mapping function enables the detection of subtle variations and relationships among the input data that might be missed by linear entropies. The method is fully data-driven and does not rely on subjective assessments, supporting transparency and reproducibility (Wen et al., 1998; Chiang & Hsieh, 2009). It also performs well with incomplete or imprecise data, which increases its applicability in practical decision environments. The non-linear structure further reduces the risk that a single highly variable criterion will dominate the weighting process, resulting in more equitable weights.

Despite these strengths, Wen entropy also presents limitations. Its non-linear formulation increases computational complexity and may lead to a greater amount of computational resources than standard entropy approaches (Chiang & Hsieh, 2009). This complexity could become a challenge for large datasets where simplicity is important.

Since both entropy-based methods have their own advantages and limitations, the following section introduces a hybrid weighting scheme that integrates Shannon and Wen entropy in one framework.

3.3.3 Hybrid Entropy Weighting

This study employs a hybrid entropy weighting scheme that integrates Shannon and Wen entropy to strengthen the robustness and objectivity of the MCDM weighting process. To create (ϕ, λ) feasible mixing criteria weights, the parameters are defined such that $\phi, \lambda \in [0, 1]$ and $\lambda = 1 - \phi$. These parameters determine the relative influence of the two entropy measures on the final weights. The

combined weight $W_j(\phi, \lambda)$ for criterion j is expressed as:

$$W_j(\phi,\lambda) = \frac{\phi}{\phi+\lambda}\left(\frac{1+\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij}\ln r_{ij}}{n+\sum_{j=1}^{n}\left(\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij}\ln r_{ij}\right)}\right) + \frac{\lambda}{\phi+\lambda}\left(\frac{\frac{1}{n-E}[1-e_j]}{\sum_{j=1}^{n}\frac{1}{n-E}[1-e_j]}\right) \tag{3.22}$$

This formulation shows a weighted average of the entropy weights derived from Shannon and Wen approaches. When ϕ is larger, the combined weight is more strongly influenced by Shannon entropy and when λ is larger, Wen entropy has greater influence. Adjusting ϕ and λ allows analysts to emphasize different characteristics of the data depending on the decision context.

Special Cases:

- **Case 1:** $\phi = 0$

  Weights depend entirely on Wen entropy:

$$W_j(\lambda) = \frac{\frac{1}{n-E}[1-e_j]}{\sum_{j=1}^{n}\frac{1}{n-E}[1-e_j]}$$

- **Case 2:** $\lambda = 0$

  Weights depend entirely on Shannon entropy:

$$W_j(\phi) = \frac{1+\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij}\ln r_{ij}}{n+\sum_{j=1}^{n}\left(\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij}\ln r_{ij}\right)}$$

The hybrid entropy approach has many benefits to offer. The linear variability measure of Shannon entropy, along with the non-linear sensitivity of Wen entropy, are the core aspects of this method, which together offer a more comprehensive assessment of criterion importance. Shannon entropy captures general variability in the data, while Wen entropy incorporates non-linear relationships and is well-suited for imprecise or incomplete datasets (Shannon, 1948; Wen et al.,

1998). Integrating the two methods allows the model to account for a broader range of information patterns.

The hybrid approach also reduces the limitations of relying solely on one entropy method. A single weighting technique may be overly influenced by specific data distributions or structural assumptions. Hybridization reduces this risk and produces more stable and consistent weighting outcomes (Wu, 2022).

The flexibility of the hybrid approach is another benefit. Decision-makers can adjust the mixing parameters based on the different analytical priorities, making the method suitable for complex decision environments such as healthcare resource evaluation.

Finally, the method enhances transparency and reproducibility. The weights are generated by explicit formulas that incorporate the mixing parameters ϕ and λ, thereby making it possible to clearly document how trade-offs were determined and allowing results to be independently verified.

After establishing the hybrid weighting scheme, the next section explains how methodological validity and reliability are ensured by data management practices, cross-validation, and reproducible computational procedures.

3.4 Methodological Validity and Reliability

Ensuring methodological validity and reliability is essential for producing credible, accurate, and reproducible quantitative research (Heale & Twycross, 2015). This study employs several measures to enhance the transparency and reliability, including the use of multiple computational tools, cross-verification of analytical outputs, and detailed documentation of data and code to support independent replication (Peng, 2011).

Two primary software environments were used for data management, computation, and verification: Microsoft Excel and Python.

Microsoft Excel was used for initial data entry, matrix construction, and verification of intermediate calculations. Its tabular structure and built-in computational functions facilitated the implementation of the TOPSIS and entropy weighting steps, allowing intermediate values to be inspected directly.

Excel's stepwise computation enabled consistent tracking of operations and helped identify potential inconsistencies during early stages of analysis (Baier & Neuwirth, 2007).

Python was as the main environment for advanced computation, automation, and visualization. Its scientific libraries supported the full analytical workflow, including data processing, entropy weight generation, and the TOPSIS ranking procedure (Yadav et al., 2019).

Using more than one analytical platform to independently replicate results is a recognized approach for identifying computational errors and improving reliability in quantitative studies (Peng, 2011). In this research, key outputs, such as entropy weights, normalized matrices, and final rankings, were computed separately in Excel and Python. The results were then compared and any discrepancies were examined, traced to their source, and resolved, ensuring that the final outputs were accurate (Leek & Peng, 2015).

To promote transparency and reproducibility, all Python code used for calculating Shannon entropy, Wen entropy, and TOPSIS is included in the Appendix. This dual-platform strategy enhances methodological rigor and demonstrates a strong commitment to best practices in quantitative research.

Together, these practices ensure that the analysis is both objective and replicable. By implementing a hybrid-entropy-weighted modified TOPSIS model and validating results through cross-platform comparison, this study establishes a reliable methodological foundation. The next chapter describes the data collection procedures and the construction of the decision matrix, which form the basis for the empirical evaluation.

Chapter IV: Data Collection

The reliability of a multi-criteria decision-making (MCDM) analysis depends on the quality and integrity of its input data. Inaccurate, incomplete, or biased information can skew the results and reduce the credibility of the decision-making process (Velasquez & Hester, 2013). Given the rapidly evolving nature of the COVID-19 pandemic and the diversity of available vaccine technologies, it is necessary to use a systematic and rigorous data collection process for meaningful evaluation and informed decision-making (Mathieu et al., 2024; Kandulu et al., 2024). Accordingly, this study adopted a structured, multi-source data collection strategy to support reliability, objectivity, and relevance in evaluating vaccine alternatives.

Recent research highlights that inclusion of data from multiple authoritative sources, such as peer-reviewed scientific literature, international health databases, and official manufacturer reports, increases the strength of vaccine comparisons and reduces the bias (Soheili et al., 2023). It is crucial to maintain a high level of transparency and accuracy in the data collection process, especially in cases where the results might lead to policies affecting the public health outcomes (WHO, 2022).

This chapter outlines how data were identified, sourced, extracted, verified, and prepared for analysis. It details the construction of a representative decision matrix that reflects the performance of each vaccine across key public health criteria. The chapter explains the rationale for selecting specific vaccines and criteria, describes the data sources used, and presents the procedures employed to ensure accuracy and consistency during data preparation. This systematic approach establishes a transparent and reproducible foundation for the multi-criteria evaluation of COVID-19 vaccines presented in the subsequent sections.

4.1 Search Strategy and Source Selection

Data for this thesis were collected from multiple authoritative sources to ensure accuracy, relevance, and global applicability. This section describes the primary sources and the rationale for their selection.

4.1.1 Peer-Reviewed Scientific Literature

Peer-reviewed journal articles were the primary source for clinical and epidemiological information about COVID-19 vaccines. The literature searches focused on leading journals such as *The Lancet*, *New England Journal of Medicine*, *Nature*, and *Annals of Clinical Microbiology and Antimicrobials*. Relevant studies included:

- Randomized controlled trials for reporting vaccine efficacy and effectiveness.
- Meta-analyses for summarizing side-effect profiles and safety outcomes.
- Research examining cross-protection against variants such as Delta and Omicron.

These sources were selected for their methodological rigor, transparent reporting standards, and established influence in global health research.

4.1.2 Global Health Authorities

International organizations offer information about vaccine performance, approval status, and safety that is constantly updated and standardized. The World Health Organization (WHO) vaccine dashboard, situation reports, and Emergency Use Listing (EUL) database were used to collect:

- Regulatory approval status and major milestones.
- Minimum age eligibility recommendations.
- Reported adverse events and safety guidance.

Additional technical details, such as dosing schedules, storage requirements, and booster recommendations, were obtained from the U.S. Centers for Disease Control and Prevention (CDC) and the European Medicines Agency (EMA).

4.1.3 National Government and Health Ministry Reports

Government health agencies often publish technical briefs, surveillance reports, and distribution data. Examples include:

- Public Health Agency of Canada, which provides technical documents on storage, shelf life, and procurement costs.
- The UK Health Security Agency (formerly Public Health England), which reports real-world vaccine performance, uptake, and safety surveillance.

When discrepancies occurred between national and international sources, the most recent and contextually relevant information was used.

4.1.4 Manufacturer Data Sheets and Press Releases

Pharmaceutical manufacturers such as Pfizer-BioNTech, Moderna, and AstraZeneca publish clinical trial updates, technical documents, and regulatory submissions. These were used to collect:

- Storage temperature and stability requirements.
- Dosage schedules, including primary and booster series.
- Information on production capacity, distribution, and cost per dose.

Manufacturer publications were especially useful when peer-reviewed studies lagged behind real-time updates or when new vaccine formulations were introduced.

4.1.5 Inclusion Criteria and Data Selection Process

To ensure methodological consistency, data were included only if they met the following requirements:

- Published or officially released between January 2020 and June 2025.

- Originated from peer-reviewed journals, government agencies, or internationally recognized institutions.

- Included transparent methodology and clearly documented data sources.

When multiple sources reported the same information, preference was given to the most recent, comprehensive, and methodologically robust evidence.

With the data sources established, the next step involved identifying the vaccine alternatives and determining the criteria used to evaluate them.

4.2 Selection of Vaccines and Criteria

Utilizing an MCDM framework for the assessment of COVID-19 vaccines requires the careful selection of both vaccine candidates and relevant evaluation criteria. This careful selection ensures that the analysis reflects real-world conditions and addresses key public health considerations. Selected vaccines must represent the diversity of technologies and global distribution patterns observed during the pandemic, while evaluation criteria must capture the clinical, logistical, and policy-related factors that influence the adoption of the vaccines. This section describes the methodology and rationale for selecting both vaccine alternatives and evaluation criteria.

4.2.1 Selection of Vaccine Alternatives

Vaccine alternatives were selected based on several considerations to ensure global relevance, scientific validity, and practical applicability. The wide range of vaccine technologies and deployment strategies led the selection process to emphasize diversity in scientific platforms, regulatory status, and geographic distribution. The main selection criteria were:

- **Availability of Published Data:** Vaccines were included only when reliable and current data were available for all major evaluation criteria, such as efficacy, safety, logistics, and cost. Priority was given to vaccines with peer-reviewed publications or comprehensive regulatory documentation.

- **Technological Diversity:** The selection includes vaccines using different scientific platforms, such as mRNA, viral vector, inactivated virus, and protein subunit, to reflect the range of technologies.

- **Global Usage and Policy Impact:** Vaccines that were widely used across multiple regions or played a key role in national or international vaccination strategies were prioritized.

Based on these criteria, the following COVID-19 vaccines were selected for analysis: **Pfizer-BioNTech (BNT162b2)**, **Moderna (mRNA-1273)**, **Johnson & Johnson (Ad26.COV2.S)**, **AstraZeneca (ChAdOx1-S)**, **Sputnik V (Gam-COVID-Vac)**, **Sinopharm (BBIBP-CorV)**, **Sinovac (CoronaVac)**, **Covaxin (BBV152)**, and **Novavax (NVX-CoV2373)**. This selection indicates a broad range of global vaccine platforms and includes vaccines that had significant public health relevance during the pandemic (Soheili et al., 2023; Kandulu et al., 2024).

4.2.2 Selection of Evaluation Criteria

The reliability of an MCDM framework depends on identifying evaluation criteria that are relevant, measurable, and aligned with real-world policy and operational needs. For this study, criteria were selected through:

- A detailed review of peer-reviewed scientific literature and health policy documents.

- Guidelines from major public health authorities (e.g., WHO, CDC).

- Empirical evidence from vaccine deployment and implementation.

The following criteria were included:

1. **Efficacy Rate:** The decrease in symptomatic COVID-19 cases among people who got vaccinated versus those who did not, based on clinical trials and real-world studies (Soheili et al., 2023; Gajpal et al., 2022).

2. **Safety and Side Effect Profile:** Frequency and severity of reported side effects, ranging from mild reactions to rare but serious adverse events. Comprehensive safety information is essential for assessing risk (Gee et al., 2021).

3. **Shelf Life and Storage Requirements:** The duration for which a vaccine remains stable under recommended storage conditions, particularly standard refrigeration ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$). This factor strongly affects the feasibility of distribution, especially in settings with limited cold-chain capacity (WHO, 2021).

4. **Number of Doses Required:** Includes the total number of doses needed for full vaccination as well as recommended boosters. Vaccines requiring fewer doses may improve overall coverage and reduce logistical demands (Public Health Agency of Canada, 2025).

5. **Cross-Protection Against Variants:** The degree to which a vaccine remains effective against major SARS-CoV-2 variants, such as Delta and Omicron, based on clinical and observational data (Cromer et al., 2022).

6. **Regulatory Approval Status:** Authorization or approval from major regulatory bodies such as the WHO, EMA, and FDA. WHO approval was particularly considered because of its importance for global distribution and acceptance (WHO, n.d.).

7. **Age Eligibility:** The lowest approved age for vaccination, based on clinical trial data and regulatory guidance. Broader age eligibility increases vaccine coverage and influences public health planning (Kandulu et al., 2024).

8. **Cost per Dose:** The procurement cost of a single vaccine dose, based on publicly available contracts, government reports, and manufacturer disclosures. Cost directly affects affordability and equitable access (Wouters et al., 2021).

Together, these criteria capture clinical performance, ease of operation, and policy considerations. They provide a comprehensive basis for evaluating vaccine alternatives in accordance with the needs

of public health authorities, policymakers, and supply chain stakeholders (Kandulu et al., 2024; Soheili et al., 2023).

4.3 Data Extraction and Curation Workflow

This section describes the systematic process followed to gather, validate, and prepare the data used in the evaluation of COVID-19 vaccines. For each vaccine and evaluation criterion, information was collected from reliable sources, validated for accuracy, and organized in a consistent format to allow meaningful comparisons. These steps ensured that the final decision matrix was robust, transparent, and suitable for multi-criteria analysis.

4.3.1 Vaccine Data Profiles

- **Pfizer-BioNTech** is an mRNA vaccine and was among the first to receive emergency authorization globally (WHO, 2022). Clinical trials reported an efficacy of approximately 95% against symptomatic COVID-19 (Polack et al., 2020; Gammudi, 2023). Common side effects include injection-site pain, fatigue, and mild to moderate systemic symptoms (Dighriri et al., 2022; Hause et al., 2022; Alamer et al., 2021). The vaccine has a shelf life of about 10 weeks under standard refrigeration ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$), although long-term storage requires ultra-cold temperatures (Ministry of Health [Ontario], 2024; CDC, 2024). The vaccine is administered as a two-dose regimen and studies indicate strong protection against variants including Delta and Omicron (Pfizer Inc., 2022; Yung et al., 2023; Bartsch et al., 2022; Bian et al., 2022). It is authorized for individuals aged six months and older (CDC, 2024; FDA, 2022), and the cost per dose typically ranges from $14 to $23, depending on procurement arrangements (Light & Lexchin, 2021; Kollewe, 2021).

- **Moderna** is an mRNA vaccine with an efficacy of approximately 94.1% against symptomatic COVID-19 (Baden et al., 2021; Gammudi, 2023). Its side effect profile is similar to that of Pfizer-BioNTech, with mild to moderate reactions such as injection-site pain, fatigue, and

headache commonly reported (CDC, 2025; Gee, 2021). Moderna remains stable for up to two months under refrigeration (2 °C to 8 °C) (CDC, 2023). The vaccine is administered in two doses several weeks apart (Health Canada, 2024; CDC, 2024). Studies indicate strong protection against major variants, including Delta and Omicron (Luczkowiak et al., 2023; Tseng et al., 2022; Gilbert et al., 2022). It is authorized by the WHO and approved for use in individuals aged six months and older in many countries (WHO, 2021; CDC, 2024; FDA, 2024).The cost per dose typically range from $15 to $37, depending on the region (Light & Lexchin, 2021).

- **Johnson & Johnson** is a viral vector vaccine notable for its single-dose regimen, which is beneficial for large-scale or rapid vaccination campaigns (Sadoff et al., 2021). Clinical studies report an efficacy of 66% against moderate to severe COVID-19 (Sadoff et al., 2021; Johnson & Johnson Inc., 2021). Side effects range from mild to severe, and studies have documented a higher incidence of rare adverse events such as blood clotting disorders and Guillain-Barré syndrome (an autoimmune disorder in which immune system attacks the nerves and causes paralysis) compared with other COVID-19 vaccines (Shay, 2021; FDA & CDC, 2021). The vaccine remains stable for up to 11 months under standard refrigeration (2 °C to 8 °C) (Johnson & Johnson Inc., 2021). Cross-protection is moderate against variants such as Delta and lower against Omicron without a booster dose (Corchado-Garcia et al., 2021; Karim & Karim, 2021). It is authorized by the WHO and approved for adults aged 18 and older in many countries (Johnson & Johnson Inc., 2022; WHO, 2021). The cost per dose is estimated between $8 and $10 (Light & Lexchin, 2021).

- **AstraZeneca** is a viral vector vaccine developed by the University of Oxford and has an efficacy of approximately 72% against symptomatic COVID-19 (Voysey et al., 2021; WHO, 2021). Reported side effects range from mild to severe, including a higher risk of rare adverse events such as blood clotting disorders and Guillain-Barré syndrome (EMA, 2021; Bazrafshan et al., 2022). It is stable for at least six months under standard refrigeration (EMA, 2021;

MHRA, 2023). The vaccine is administered in a two-dose schedule (Falsey et al., 2021; AstraZeneca Inc., 2021). Cross-protection is moderate for the Delta variant but reduced for Omicron (Madhi et al., 2023; Andrews et al., 2022; Meeraus et al., 2023). AstraZeneca is approved by the WHO and commonly authorized for adults aged 18 and older (WHO, 2021; Health Canada, 2021). Its cost per dose is relatively low, typically $2 to $5 (Kollewe, 2021).

- **Sputnik V** is a viral vector vaccine developed by the Gamaleya Research Institute in Russia. It is administered in two doses (The Gamaleya Research Centre, 2021; Jones & Roy, 2021). Russian clinical trial data report an efficacy of 91.6% against symptomatic COVID-19 (Logunov et al., 2021; The Gamaleya Research Centre, 2020). Reported side effects are similar to those of other viral vector vaccines and include a higher risk of rare adverse events such as blood clotting disorders and Guillain-Barré syndrome (Di Valerio et al., 2022; Selbe & Podlutsky, 2024; Babamahmoodi et al., 2021). Sputnik V has a shelf life of approximately six months when stored at $2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$ (The Gamaleya Research Centre, 2021; National Institutes of Health, Islamabad, 2021). It is authorized for adults aged 18 and older in more than 70 countries, although it has not been approved by the WHO (WHO, 2023; Montalti et al., 2021). Studies indicate moderate cross-protection against variants such as Delta, with reduced protection against Omicron (Ikegame et al., 2021; Franco et al., 2024; Sukhikh et al., 2022). The cost per dose is approximately $10 (The Gamaleya Research Centre, 2020).

- **Sinopharm** is an inactivated virus vaccine developed by the Beijing Institute of Biological Products in China. Studies have reported an efficacy rate of approximately 79% in preventing symptomatic COVID-19 (Al Kaabi et al., 2021; WHO, 2022). Reported side effects are generally mild, with most recipients experiencing local or short reactions such as pain in the injection site or fatigue (WHO, 2022; Haider et al., 2023; Mirnia et al., 2024). The vaccine has a shelf life of up to 24 months when stored at standard refrigeration temperatures ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$), which supports its distribution in settings with limited cold-chain capacity (WHO, 2022). It is administered in a two-dose regimen, with booster doses recommended as

additional variants emerge (Sage, 2021; WHO, 2022). Sinopharm has received emergency use authorization from the WHO and is approved for individuals aged 18 years and older (WHO, 2022). Studies indicate lower cross-protection against variants such as Omicron compared with mRNA or viral vector vaccines, often requiring booster doses to sustain immunity (Sage, 2021; Al Kaabi et al., 2021; Belayachi et al., 2024). The cost per dose generally ranges from $10 to $30, depending on procurement agreements (Irurzun-Lopez, 2023).

- **Sinovac** is an inactivated virus vaccine produced by Sinovac Biotech. Reported efficacy varies across studies, with an overall effectiveness of approximately 51% in preventing symptomatic COVID-19 (Tanriover et al., 2021; WHO, 2022). Reported side effects are typically mild and include local reactions and short-duration fever (Masood et al., 2023; Ramatillah et al., 2024; Riad et al., 2021). The vaccine has a shelf life of up to 12 months at standard refrigeration temperatures ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$) (PAHO, n.d.; WHO, 2021). It is administered as a two-dose regimen, with booster doses often recommended to maintain protection (WHO, 2022). Sinovac has been granted WHO emergency use listing for adults aged 18 and older and has been widely used in Latin America and Asia (WHO, 2021; WHO, 2022). Available evidence indicates reduced cross-protection against variants such as Omicron, making booster doses important for sustaining immunity (Jara et al., 2021; Li et al., 2022; Zhao et al., 2022). Reported costs range from $13 to $29 per dose (Irurzun-Lopez, 2023).

- **Covaxin** is an inactivated virus vaccine developed by Bharat Biotech in collaboration with the Indian Council of Medical Research. Clinical trial data report an efficacy of approximately 77.8% in preventing symptomatic COVID-19 (Ella et al., 2021; Bharat Biotech International Limited, 2021). Reported side effects are generally mild, most commonly including injection-site pain and low-grade fever (Ella et al., 2021; WHO, 2022; Kaur et al., 2022). Covaxin remains stable for up to nine months at standard refrigeration temperatures ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$) (WHO, 2022). It is administered as a two-dose regimen, with booster doses recommended in response to emerging variants (WHO, 2022). Evidence indicates some cross-protection

against variants, although effectiveness decreases against Omicron (Patil et al., 2023; Yadav et al., 2022; Bharat Biotech International Limited, 2022). Covaxin has received WHO emergency use authorization and is approved in a number of countries, particularly in South Asia and parts of Africa, for adults aged 18 and older (WHO, 2021; WHO, 2022). Reported costs range from $10 to $15 per dose (Sharma & Pandey, 2021).

- **Novavax** is a protein subunit vaccine developed by the American biotechnology company Novavax. Clinical trials have reported an efficacy rate of approximately 90% against symptomatic COVID-19 (Heath et al., 2021). Reported side effects are generally mild, including injection-site pain and short-duration fever (CDC, 2022; Heath et al., 2021; Dadras et al., 2022). Novavax remains stable for up to nine months at standard refrigeration temperatures ($2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$) (WHO, 2022). It is administered in a two-dose schedule, with booster doses recommended as additional variants circulate (CDC, 2023; FDA, 2022). Several studies indicate strong cross-protection against major variants such as Delta and Omicron, making it a widely used non-mRNA alternative (Shinde et al., 2021; Bhiman et al., 2023; Anez et al., 2025). Novavax has received WHO authorization and is commonly approved for individuals aged 12 years and older (WHO, 2021; CDC, 2023). The cost per dose generally ranges from $16 to $18 (WHO, 2022).

After compiling the vaccine data, Table 2 summarizes and compares all vaccines based on the key evaluation criteria. This summary forms the basis for constructing the decision matrix and conducting the multi-criteria analysis.

Table 2
Summary of COVID-19 Vaccine Data

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost per Dose ($)
Pfizer	95%	Moderate	2.5	2	Strong, rapid mRNA adaptability	Yes	0.5	14–23
Moderna	94.1%	Moderate	2	2	Strong, rapid mRNA adaptability	Yes	0.5	15–37
J&J	66%	Severe	11	1	Moderate, slower adaptability	Yes	18	8–10
AstraZeneca	72%	Severe	6	2	Moderate, slower adaptability	Yes	18	2–5
Sputnik V	91.6%	Severe	6	2	Moderate, slower adaptability	No	18	10
Sinopharm	79%	Mild	24	2	Low, weak immune memory	Yes	18	10–30
Sinovac	51%	Mild	12	2	Low, weak immune memory	Yes	18	13–29
Covaxin	77.8%	Mild	9	2	Low, weak immune memory	Yes	18	10–15
Novavax	90%	Mild	9	2	Strong, stable immune response	Yes	12	16–18

4.3.2 Data Verification and Cross-Validation

To ensure the reliability and accuracy of the dataset, a structured cross-validation process was followed. After each data point was collected, it was compared with at least one additional authoritative source whenever possible. This procedure was especially important for criteria such as side effect profiles and cross-protection, as their values can differ across studies or be updated over time. By systematically comparing information from peer-reviewed publications, reports from global and national health authorities, and official manufacturer documentation, inconsistencies were identified and addressed.

When discrepancies occurred between sources, a clear selection protocol was applied. Priority was given to the most recent and comprehensive meta-analyses or systematic reviews, because these synthesize findings from multiple studies and provide a high level of evidence. If such sources were unavailable for a given criterion, the summaries from the WHO or national regulatory agencies were consulted next due to their standardized reporting and broad data access. When these sources did not provide the required information, data from original peer-reviewed clinical trials or real-world effectiveness studies were used. Manufacturer reports or press releases were referenced only when none of the previous sources included the specific data needed.

Following verification and cross-validation, the confirmed data were prepared and standardized for use in the decision matrix, ensuring consistency and comparability across all vaccine alternatives and evaluation criteria.

4.3.3 Data Adjustment

After all relevant data were collected and verified, the next step involved adjusting the information so that all vaccines and evaluation criteria could be compared in a consistent manner. This process included converting qualitative or categorical data into quantitative or ordinal values and standardizing numerical data to support accurate comparisons within the decision matrix.

To incorporate qualitative criteria, standardized coding schemes were developed based on the published literature and established MCDM practices. For example, side effect severity was coded

using an ordinal scale where mild reactions were assigned a value of one, moderate reactions a value of three, and severe reactions a value of five. This scale differentiates between degrees of severity and allows the model to quantify the relative impact of adverse events, with higher values indicating more severe outcomes. Similarly, regulatory approval status was coded as five for vaccines approved by the WHO and as one for vaccines without WHO approval, emphasizing the practical importance of regulatory validation in global vaccine deployment.

For cross-protection against variants, a scale was developed to represent both the strength of protection and the adaptability of their vaccine platform. Vaccines with strong protection and rapid adaptability (e.g., mRNA platforms) were assigned a value of five. Protein subunit vaccines with strong but less adaptable immune responses were assigned a value of four. Viral vector vaccines with moderate protection and slower adaptability received a value of three, while traditional inactivated vaccines with limited cross-protection and weaker immune memory were assigned a value of one.

All evaluation criteria have been divided into two categories, benefit or cost. Benefit criteria included efficacy rate, shelf life (at $2\,^{\circ}\mathrm{C}$ to $8\,^{\circ}\mathrm{C}$), cross-protection, and WHO approval, where higher values indicate more favorable performance. Cost criteria included side effect severity, number of doses required, age eligibility, and cost per dose, for which lower values are preferred. To estimate total vaccination cost, cost per dose was multiplied by the number of required doses, and this total cost value was used in the decision matrix. For criteria reported as ranges due to regional or market variation, the mean value was used in order to ensure that the dataset remained consistent.

This data adjustment process transformed all vaccine alternatives and criteria into a standardized numerical format, providing a consistent basis for the subsequent multi-criteria evaluation.

4.3.4 Construction of the Decision Matrix

All processed and adjusted data were organized into a structured decision matrix, where each row represented a different vaccine and each column represented an evaluation criterion. Table 3 served as the foundational input for our model.

Table 3
Standardized Decision Matrix for COVID-19 Vaccine Alternatives

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	0.95	3	2.5	2	5	5	0.5	37
Moderna	0.941	3	2	2	5	5	0.5	52
J & J	0.66	5	11	1	3	5	18	9
AstraZeneca	0.72	5	6	2	3	5	18	7
Sputnik V	0.916	5	6	2	3	1	18	20
Sinopharm	0.79	1	24	2	1	5	18	40
Sinovac	0.51	1	12	2	1	5	18	42
Covaxin	0.778	1	9	2	1	5	18	25
Novavax	0.9	1	9	2	4	5	12	34

4.4 Ethical Considerations and Limitations

The research for this study was entirely based on secondary data that were sourced only from publicly accessible scientific publications, health authorities' official reports, and manufacturers' documentation. No primary data were collected from human participants which eliminated any concerns related to privacy or confidentiality. All procedures followed standard research practices and were consistent with institutional and international ethical guidelines.

Although considerable efforts were taken to gather comprehensive and up-to-date information, certain limitations remain. The evolving characteristics of the pandemic mean that the latest findings could not be included in the available literature at the time of analysis. Differences in data reporting standards across countries may cause additional uncertainty. In some cases, limited or incomplete data for newer vaccine candidates or specific population groups may affect the generalization of the findings. An additional limitation is the conversion of qualitative information into quantitative form, as this process involves simplification and may reduce detail. These constraints were acknowledged and, where possible, addressed through cross-checking information from multiple independent

sources.

Chapter V: Numerical Analysis and Results

In this chapter, the numerical analysis of the COVID-19 vaccine selection problem is carried out in a detailed, step-by-step manner, using the hybrid-entropy-weighted modified TOPSIS framework developed in previous chapters. The process consists of several stages: it begins with the computation of Shannon entropy weights and the corresponding TOPSIS rankings; next, it calculates Wen entropy weights and their corresponding rankings; finally, it includes a comparative evaluation of the hybrid weighting scheme across various mixing parameters. All computational steps were carried out using Python and Excel. This dual-platform approach enhances the reliability of the results, reduces the potential for manual or software-specific errors, and ensures full reproducibility of the numerical analysis.

To provide a foundation for the analysis, Table 4 displays the complete decision matrix for the empirical study.

Table 4
Decision Matrix

	Max Benefit	**Min cost**	**Max Benefit**	**Min cost**	**Max Benefit**	**Max Benefit**	**Min cost**	**Min cost**
Name	**Efficacy Rate**	**Side Effect**	**Shelf Life (mo)**	**No. of Doses**	**Cross-Protection**	**Approval by WHO**	**Age Eligibility (yr)**	**Cost ($)**
Pfizer-BioNTech	0.95	3	2.5	2	5	5	0.5	37
Moderna	0.941	3	2	2	5	5	0.5	52
J & J	0.66	5	11	1	3	5	18	9
AstraZeneca	0.72	5	6	2	3	5	18	7
Sputnik V	0.916	5	6	2	3	1	18	20
Sinopharm	0.79	1	24	2	1	5	18	40
Sinovac	0.51	1	12	2	1	5	18	42
Covaxin	0.778	1	9	2	1	5	18	25
Novavax	0.9	1	9	2	4	5	12	34

The following sections outline each step of the analysis, starting with Shannon entropy.

5.1 TOPSIS Ranking Using Shannon Entropy Weights

Shannon entropy is widely adopted in MCDM due to its ability to offer objective weights based on the diversity and distribution of criterion data. In the first phase, Shannon entropy method is used to determine the objective weights for each criterion. These weights are then applied in the TOPSIS method to rank the alternatives.

Step 1: Calculating Shannon Entropy

The normalized decision matrix is constructed from Table 4 using Equation 3.10. The resulting normalized matrix is displayed in Table 5.

Table 5
Normalized Decision Matrix for Shannon Entropy

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	0.1326	0.1200	0.0307	0.1176	0.1923	0.1220	0.0041	0.1391
Moderna	0.1313	0.1200	0.0245	0.1176	0.1923	0.1220	0.0041	0.1955
J & J	0.0921	0.2000	0.1350	0.0588	0.1154	0.1220	0.1488	0.0338
AstraZeneca	0.1005	0.2000	0.0736	0.1176	0.1154	0.1220	0.1488	0.0263
Sputnik V	0.1278	0.2000	0.0736	0.1176	0.1154	0.0244	0.1488	0.0752
Sinopharm	0.1103	0.0400	0.2945	0.1176	0.0385	0.1220	0.1488	0.1504
Sinovac	0.0712	0.0400	0.1472	0.1176	0.0385	0.1220	0.1488	0.1579
Covaxin	0.1086	0.0400	0.1104	0.1176	0.0385	0.1220	0.1488	0.0940
Novavax	0.1256	0.0400	0.1104	0.1176	0.1538	0.1220	0.0992	0.1278

With the normalized matrix established, the next step is to compute the entropy E_j for each criterion, also $\frac{1}{\ln 9} = 0.4551$.

$$E_j = -\frac{1}{\ln 9}\sum_{i=1}^{9} r_{ij}\ln r_{ij}, \qquad \forall,\ i = 1, 2\ldots, 9,\ j = 1, 2\ldots, 8 \tag{5.23}$$

Having calculated the entropy values, we determine the degree of diversification $d_j = 1 - E_j$ and derive the final weights based on Equation 3.14.

Table 6 summarizes the results of the entropy values E_j, degrees of diversification d_j, and the corresponding weights.

Table 6
Shannon Entropy

	Efficacy Rate	**Side Effect**	**Shelf Life (mo)**	**No. of Doses**	**Cross-Protection**	**Approval by WHO**	**Age Eligibility (yr)**	**Cost ($)**
E	0.9926	0.9055	0.9016	0.9925	0.9310	0.9755	0.8990	0.9375
D	0.0074	0.0945	0.0984	0.0075	0.0690	0.0245	0.1010	0.0625
Weight	0.0160	0.2033	0.2117	0.0160	0.1485	0.0527	0.2173	0.1345

Step 2: Normalizing the Decision Matrix for TOPSIS

After calculating the Shannon criterion weights, the decision matrix in Table 4 is normalized using the TOPSIS procedure, as described in Equation 3.2.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1, 2, \ldots, 9, \quad j = 1, 2, \ldots, 8 \tag{5.24}$$

Table 7 shows this normalized decision matrix.

Table 7
Normalized Decision Matrix for TOPSIS

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	0.3918	0.3046	0.0759	0.3482	0.5103	0.3527	0.0109	0.3748
Moderna	0.3880	0.3046	0.0607	0.3482	0.5103	0.3527	0.0109	0.5267
J & J	0.2722	0.5077	0.3339	0.1741	0.3062	0.3527	0.3939	0.0912
AstraZeneca	0.2969	0.5077	0.1821	0.3482	0.3062	0.3527	0.3939	0.0709
Sputnik V	0.3777	0.5077	0.1821	0.3482	0.3062	0.0705	0.3939	0.2026
Sinopharm	0.3258	0.1015	0.7285	0.3482	0.1021	0.3527	0.3939	0.4051
Sinovac	0.2103	0.1015	0.3643	0.3482	0.1021	0.3527	0.3939	0.4254
Covaxin	0.3208	0.1015	0.2732	0.3482	0.1021	0.3527	0.3939	0.2532
Novavax	0.3711	0.1015	0.2732	0.3482	0.4082	0.3527	0.2626	0.3444

Step 3: Constructing the Weighted Normalized Decision Matrix

Based on Equation 3.3, we have:

$$V = (v_{ij})_{9\times 8} = w_j r_{ij} = \begin{bmatrix} w_1 r_{1\times 1} & w_2 r_{1\times 2} & \dots & w_8 r_{1\times 8} \\ w_1 r_{2\times 1} & w_2 r_{2\times 2} & \dots & w_8 r_{2\times 8} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{9\times 1} & w_2 r_{9\times 1} & \dots & w_8 r_{9\times 8} \end{bmatrix} \tag{5.25}$$

Using Tables 6 and 7, we calculated the weighted normalized decision matrix which is shown in Table 8.

Table 8
Weighted (Shannon) Normalized Decision Matrix

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	0.0063	0.0619	0.0161	0.0056	0.0758	0.0186	0.0024	0.0504
Moderna	0.0062	0.0619	0.0129	0.0056	0.0758	0.0186	0.0024	0.0708
J & J	0.0043	0.1032	0.0707	0.0028	0.0455	0.0186	0.0856	0.0123
AstraZeneca	0.0047	0.1032	0.0386	0.0056	0.0455	0.0186	0.0856	0.0095
Sputnik V	0.0060	0.1032	0.0386	0.0056	0.0455	0.0037	0.0856	0.0272
Sinopharm	0.0052	0.0206	0.1542	0.0056	0.0152	0.0186	0.0856	0.0545
Sinovac	0.0034	0.0206	0.0771	0.0056	0.0152	0.0186	0.0856	0.0572
Covaxin	0.0051	0.0206	0.0578	0.0056	0.0152	0.0186	0.0856	0.0340
Novavax	0.0059	0.0206	0.0578	0.0056	0.0606	0.0186	0.0571	0.0463

With the weighted normalized decision matrix prepared, the next step is to identify both the ideal and negative-ideal solutions.

Step 4: Identifying Ideal and Negative-Ideal Solutions

The ideal solution (A^+) is constructed by selecting the maximum value for each benefit criterion and the minimum value for each cost criterion among the alternatives. Conversely, the negative-ideal solution (A^-) includes the minimum value for each benefit criterion and the maximum value for each cost criterion. Table 9 presents the values for both A^+ and A^- across all criteria.

Table 9
Ideal and Negative-Ideal Solutions (TOPSIS for Shannon Entropy)

	Max	Min	Max	Min	Max	Max	Min	Min
deal and Negative-Ideal Solutions	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
A^+	0.0063	0.0206	0.1542	0.0028	0.0758	0.0186	0.0024	0.0095
A^-	0.0034	0.1032	0.0129	0.0056	0.0152	0.0037	0.0856	0.0708

Step 5 and 6: Calculating Distances and Similarity to Ideal Solution

These steps involve calculating the Euclidean distances of each alternative to these ideal solutions and negative-ideal solutions by using Equations 3.6 and 3.7, respectively.

$$D_i^+ = \sqrt{\sum_{j=1}^{8} \left(v_{ij} - v_j^+\right)^2}, \qquad i = 1, 2, \ldots, 9, \; j = 1, 2, \ldots, 8 \tag{5.26}$$

$$D_i^- = \sqrt{\sum_{j=1}^{8} \left(v_{ij} - v_j^-\right)^2}, \qquad i = 1, 2, \ldots, 9 \;\; j = 1, 2, \ldots, 8 \tag{5.27}$$

Using the distances, we can now determine the relative closeness of each alternative to the ideal solution by applying Equation 3.8. The vaccines are then ranked in descending order according to their RC_i values. Table 10 displays the computed D^+, D^-, RC_i values, along with the resulting ranks for each vaccine.

Table 10
TOPSIS Ranking for Shannon Entropy

Name	D^+	D^-	RC	Rank
Pfizer-BioNTech	0.1499	0.1139	0.4317	4
Moderna	0.1595	0.1120	0.4124	6
Johnson & Johnson	0.1471	0.0890	0.3769	7
AstraZeneca	0.1675	0.0746	0.3080	8
Sputnik V	0.1691	0.0590	0.2588	9
Sinopharm	0.1124	0.1652	0.5951	1
Sinovac	0.1372	0.1066	0.4371	3
Covaxin	0.1432	0.1021	0.4162	5
Novavax	0.1178	0.1120	0.4875	2

Following the establishment of results from the Shannon entropy approach, we now apply the Wen entropy method to the same decision matrix for further analysis.

5.2 TOPSIS Ranking Using Wen Entropy Weights

While Shannon entropy focuses on data variability, Wen entropy offers a different perspective. In this section, we evaluate the alternatives using the Wen entropy weighting approach, followed by a ranking based on the TOPSIS method.

Step 1: Calculating Wen Entropy

The normalized decision matrix is derived from Table 4 using Equation 3.16. The resulting normalized matrix is shown in Table 11.

Table 11
Normalized Decision Matrix for Wen Entropy

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	1.0000	0.5000	0.0227	0.0000	1.0000	1.0000	1.0000	0.3333
Moderna	0.9795	0.5000	0.0000	0.0000	1.0000	1.0000	1.0000	0.0000
J & J	0.3409	0.0000	0.4091	1.0000	0.5000	1.0000	0.0000	0.9556
AstraZeneca	0.4773	0.0000	0.1818	0.0000	0.5000	1.0000	0.0000	1.0000
Sputnik V	0.9227	0.0000	0.1818	0.0000	0.5000	0.0000	0.0000	0.7111
Sinopharm	0.6364	1.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.2667
Sinovac	0.0000	1.0000	0.4545	0.0000	0.0000	1.0000	0.0000	0.2222
Covaxin	0.6091	1.0000	0.3182	0.0000	0.0000	1.0000	0.0000	0.6000
Novavax	0.8864	1.0000	0.3182	0.0000	0.7500	1.0000	0.3429	0.4000

Once normalization is complete, the next step is to compute the sum for each criterion column, $D_j = \sum_{i=1}^{9} r_{ij}$, and determine the normalized coefficient $K = \frac{1}{0.6487 \times 9} = 0.1713$. Using these values, we can calculate the entropy value for each criterion as follows:

$$e_j = 0.1713 \sum_{i=1}^{9} w_e \left(\frac{r_{ij}}{D_j} \right), \forall,\ i = 1, 2 \ldots, 9,\ j = 1, 2 \ldots, 8 \tag{5.28}$$

Finally, by substituting e_j and using $E = \sum_{j=1}^{8} e_j$ in Equation 3.21, we could compute W_j. The results for D_j, e_j, and the corresponding weights are summarized in Table 12.

Table 12
Wen Entropy

	Efficacy Rate	**Side Effect**	**Shelf Life (mo)**	**No. of Doses**	**Cross-Protection**	**Approval by WHO**	**Age Eligibility (yr)**	**Cost ($)**
D	5.8523	5.0000	2.8864	1.0000	4.2500	8.0000	2.3429	4.4889
e	0.3929	0.3717	0.3644	0.0000	0.3702	0.3992	0.2745	0.3833
Weight	0.1115	0.1154	0.1168	0.1837	0.1157	0.1104	0.1333	0.1133

Step 2: Normalizing the Decision Matrix for TOPSIS

Since the normalized decision matrix for TOPSIS was previously established for Shannon entropy (see Table 7), it will also be used here for the Wen entropy analysis to ensure consistency in the comparison.

Step 3: Constructing the Weighted Normalized Decision Matrix

Weighted normalization is determined by multiplying each entry of the normalized matrix by its corresponding Wen entropy weight , as shown in Equation 5.29. The resulting weighted normalized matrix can be found in Table 13.

$$V = (v_{ij})_{9\times 8} = w_j r_{ij} = \begin{bmatrix} w_1 r_{1\times 1} & w_2 r_{1\times 2} & \dots & w_8 r_{1\times 8} \\ w_1 r_{2\times 1} & w_2 r_{2\times 2} & \dots & w_8 r_{2\times 8} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{9\times 1} & w_2 r_{9\times 1} & \dots & w_8 r_{9\times 8} \end{bmatrix} \tag{5.29}$$

Table 13
Weighted (Wen) Normalized Decision Matrix

Name	Efficacy Rate	Side Effect	Shelf Life (mo)	No. of Doses	Cross-Protection	Approval by WHO	Age Eligibility (yr)	Cost ($)
Pfizer-BioNTech	0.0437	0.0352	0.0089	0.0640	0.0590	0.0389	0.0015	0.0425
Moderna	0.0433	0.0352	0.0071	0.0640	0.0590	0.0389	0.0015	0.0597
J & J	0.0304	0.0586	0.0390	0.0320	0.0354	0.0389	0.0525	0.0103
AstraZeneca	0.0331	0.0586	0.0213	0.0640	0.0354	0.0389	0.0525	0.0080
Sputnik V	0.0421	0.0586	0.0213	0.0640	0.0354	0.0078	0.0525	0.0229
Sinopharm	0.0363	0.0117	0.0851	0.0640	0.0118	0.0389	0.0525	0.0459
Sinovac	0.0235	0.0117	0.0425	0.0640	0.0118	0.0389	0.0525	0.0482
Covaxin	0.0358	0.0117	0.0319	0.0640	0.0118	0.0389	0.0525	0.0287
Novavax	0.0414	0.0117	0.0319	0.0640	0.0472	0.0389	0.0350	0.0390

With V in hand, the subsequent step specifies the ideal and negative-ideal solutions.

Step 4: Identifying Ideal and Negative-Ideal Solutions

Formally, let $A^+ = (v_1^+, \ldots, v_n^+)$ and $A^- = (v_1^-, \ldots, v_n^-)$ with $v_j^+ = \max_i v_{ij}$ for $j \in \Omega_b$ and $v_j^+ = \min_i v_{ij}$ for $j \in \Omega_c$, and analogously $v_j^- = \min_i v_{ij}$ for $j \in \Omega_b$ and $v_j^- = \max_i v_{ij}$ for $j \in \Omega_c$.

Table 14 reports A^+ and A^- by criterion.

Table 14
Ideal and Negative-Ideal Solutions (TOPSIS for Wen Entropy)

deal and Negative-Ideal Solutions	Max Efficacy Rate	Min Side Effect	Max Shelf Life (mo)	Min No. of Doses	Max Cross-Protection	Max Approval by WHO	Min Age Eligibility (yr)	Min Cost ($)
A^+	0.0437	0.0117	0.0851	0.0320	0.0590	0.0389	0.0015	0.0080
A^-	0.0235	0.0586	0.0071	0.0640	0.0118	0.0078	0.0525	0.0597

Step 5 and 6: Calculating Distances and Similarity to Ideal Solution

We now compute the separations D_i^+ and D_i^- for each alternative using Equations 3.6 and 3.7.

$$D_i^+ = \sqrt{\sum_{j=1}^{8} \left(v_{ij} - v_j^+\right)^2}, \qquad i = 1, 2, \ldots, 9,\ j = 1, 2, \ldots, 8 \tag{5.30}$$

$$D_i^- = \sqrt{\sum_{j=1}^{8} \left(v_{ij} - v_j^-\right)^2}, \qquad i = 1, 2, \ldots, 9\ \ j = 1, 2, \ldots, 8 \tag{5.31}$$

The proximity to the ideal solution for each vaccine is then determined by Equation 3.8, and the alternatives are ranked accordingly. Distances and scores has shown in Table 15.

Table 15
TOPSIS Ranking for Wen Entropy

Name	D^+	D^-	RC	Rank
Pfizer-BioNTech	0.0925	0.0840	0.4759	3
Moderna	0.1016	0.0821	0.4471	5
Johnson & Johnson	0.0876	0.0778	0.4704	4
AstraZeneca	0.1028	0.0670	0.3946	8
Sputnik V	0.1079	0.0496	0.3147	9
Sinopharm	0.0857	0.0980	0.5334	1
Sinovac	0.0984	0.0675	0.4067	7
Covaxin	0.0958	0.0700	0.4221	6
Novavax	0.0780	0.0780	0.5003	2

Having completed the analysis using Wen entropy weights, the following section introduces the hybrid entropy weighting scheme and evaluates its impact on the final rankings.

5.3 TOPSIS Ranking Using Hybrid Entropy Weights

This section explains the application of the hybrid entropy weighting scheme that flexibly combines both Shannon and Wen entropy weights for each criterion. By adjusting the mixing parameter ϕ (and $\lambda = 1 - \phi$), and repeating Steps 2-6, we systematically examine how the combination of objective weighting methods influences the final ranking of COVID-19 vaccine alternatives.

Step 1: Calculating Hybrid Entropy

The hybrid weights are determined using Equation 3.22. Given that $\phi + \lambda = 1$, we can express the equation as follows:

$$W_j(\phi, \lambda) = \phi \left(\frac{1 + \frac{1}{\ln 9} \sum_{i=1}^{9} r_{ij} \ln r_{ij}}{8 + \sum_{j=1}^{8} \left(\frac{1}{\ln 9} \sum_{i=1}^{9} r_{ij} \ln r_{ij} \right)} \right) + 1 - \phi \left(\frac{\frac{1}{8-E}[1 - e_j]}{\sum_{j=1}^{8} \frac{1}{8-E}[1 - e_j]} \right) \tag{5.32}$$

In this analysis, we vary the parameter ϕ from 0 to 1 in increments of 0.1 (i.e., $\phi = 0, 0.1, 0.2, ..., 1$). This range allows us to observe how the weighting and consequently, the ranking shifts from a pure Wen entropy weighting ($\phi = 0$) to a pure Shannon entropy weighting ($\phi = 1$). Special cases are:

- When $\phi = 0$, the hybrid weight reduces to the Wen entropy weight.

$$W_j(0, 1) = \left(\frac{\frac{1}{8-E}[1 - e_j]}{\sum_{j=1}^{8} \frac{1}{8-E}[1 - e_j]} \right) \tag{5.33}$$

- When $\phi = 1$, the weight is solely determined by the Shannon entropy method.

$$W_j(1, 0) = \left(\frac{1 + \frac{1}{\ln 9} \sum_{i=1}^{9} r_{ij} \ln r_{ij}}{8 + \sum_{j=1}^{8} \left(\frac{1}{\ln 9} \sum_{i=1}^{9} r_{ij} \ln r_{ij} \right)} \right) \tag{5.34}$$

Table 16 presents the complete set of criterion weights associated with each value of ϕ.

Table 16
Hybrid Entropy Weights

ϕ	$\lambda = 1 - \phi$	**Efficacy Rate**	**Side Effect**	**Shelf Life (mo)**	**No. of Doses**	**Cross-Protection**	**Approval by WHO**	**Age Eligibility (yr)**	**Cost ($)**
0	1 (Wen)	0.1115	0.1154	0.1168	0.1837	0.1157	0.1104	0.1333	0.1133
0.1	0.9	0.1020	0.1242	0.1262	0.1669	0.1190	0.1046	0.1417	0.1154
0.2	0.8	0.0924	0.1330	0.1357	0.1502	0.1223	0.0988	0.1501	0.1175
0.3	0.7	0.0829	0.1418	0.1452	0.1334	0.1255	0.0931	0.1585	0.1196
0.4	0.6	0.0733	0.1506	0.1547	0.1166	0.1288	0.0873	0.1669	0.1218
0.5	0.5	0.0637	0.1594	0.1642	0.0999	0.1321	0.0815	0.1753	0.1239
0.6	0.4	0.0542	0.1682	0.1737	0.0831	0.1354	0.0758	0.1837	0.1260
0.7	0.3	0.0446	0.1769	0.1832	0.0663	0.1387	0.0700	0.1921	0.1281
0.8	0.2	0.0351	0.1857	0.1927	0.0496	0.1420	0.0642	0.2005	0.1302
0.9	0.1	0.0255	0.1945	0.2022	0.0328	0.1452	0.0585	0.2089	0.1323
1	0 (Shannon)	0.0160	0.2033	0.2117	0.0160	0.1485	0.0527	0.2173	0.1345

Each row of Table 16 represents a unique set of weights for which the TOPSIS ranking procedure is repeated, enabling a comprehensive comparison across the entire range of possible combinations.

Step 2: Normalizing the Decision Matrix for TOPSIS

As previously established in the Shannon entropy section, the normalized decision matrix for TOPSIS (see Table 7) is consistently used here to enable a fair and direct comparison of ranking results under all weighting scenarios.

Step 3: Constructing the Weighted Normalized Decision Matrix

For each set of hybrid weights, the entries in the normalized matrix are multiplied by their corresponding weights (see Equation 3.3) to create a new weighted normalized decision matrix.

Step 4: Identifying Ideal and Negative-Ideal Solutions

Ideal (A^+) and negative-ideal (A^-) solutions are determined as follows.

$$A^+ = \{\max_i v_{ij} \mid j \in \Omega_b;\ \min_i v_{ij} \mid j \in \Omega_c\} = \left(v_1^+, \ldots, v_n^+\right) \tag{5.35}$$

$$A^- = \{\min_i v_{ij} \mid j \in \Omega_b;\ \max_i v_{ij} \mid j \in \Omega_c\} = \left(v_1^-, \ldots, v_n^-\right) \tag{5.36}$$

Step 5 and 6: Calculating Distances and Similarity to Ideal Solution

The Euclidean distances to both ideal and negative-ideal solutions are calculated using Equations 3.6 and 3.7. Using these distances, relative closeness follows as $RC_i = \dfrac{D_i^-}{D_i^+ + D_i^-}$. Afterwards, alternatives are ranked in descending order based on the values of RC_i for each value of ϕ. Table 17 summarizes the TOPSIS rankings for all vaccine alternatives as the mixing parameter ϕ varies from 0 (Wen) to 1 (Shannon).

Table 17
TOPSIS Ranking for Hybrid Entropy Weights

#	Wen	$\phi = 0.1$	$\phi = 0.2$	$\phi = 0.3$	$\phi = 0.4$	$\phi = 0.5$	$\phi = 0.6$	$\phi = 0.7$	$\phi = 0.8$	$\phi = 0.9$	Shannon
1	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha	Sinopha
2	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax	Novavax
3	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Pfizer	Sinovac	Sinovac
4	J & J	J & J	J & J	Moderna	Moderna	Sinovac	Sinovac	Sinovac	Sinovac	Pfizer	Pfizer
5	Moderna	Moderna	Moderna	J & J	Sinovac	Moderna	Moderna	Moderna	Moderna	Covaxin	Covaxin
6	Covaxin	Covaxin	Covaxin	Sinovac	Covaxin	Covaxin	Covaxin	Covaxin	Covaxin	Moderna	Moderna
7	Sinovac	Sinovac	Sinovac	Covaxin	J & J	J & J	J & J	J & J	J & J	J & J	J & J
8	Astra	Astra	Astra	Astra	Astra	Astra	Astra	Astra	Astra	Astra	Astra
9	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik	Sputnik

This hybrid analysis enables us to systematically assess the sensitivity of vaccine rankings to the choice and mixture of entropy-based weighting schemes. By exploring the variations in rankings from Wen entropy to Shannon entropy, our findings provide valuable insights into the robustness, flexibility, and practical implications of the proposed decision model for prioritizing public health initiatives.

After establishing the rankings under all weighting scenarios, the next chapter will analyze and interpret these results, as well as explore their practical implications for public health decision-making.

Chapter VI: Discussion

This chapter analyzes the results of the modified TOPSIS model under Shannon entropy, Wen entropy, and a hybrid entropy weighting strategy, using different mixing parameters (ϕ, λ) ranging from 0 to 1. The objective is to examine how different weighting schemes affect vaccine rankings and identify situations in which each weighting strategy provides the most relevant decision support. The analysis shows consistent patterns in the relative positions of some vaccines, differences between clinically oriented and logistically oriented rankings, and their implications for pandemic management.

6.1 Interpretation of Shannon Entropy Weights and Rankings

The first step in analysis involves interpreting the outcomes of the Shannon entropy weighting method and the corresponding TOPSIS ranking results. While the previous chapter presented these results in numerical form, this section focuses on explaining the patterns behind the findings. The goal is to clarify why certain criteria received higher weights, how these weights influenced the vaccine rankings, and what these findings indicate about the characteristics of the Shannon-based approach. This interpretation provides a basis for comparing these results with those obtained from other weighting methods in later sections.

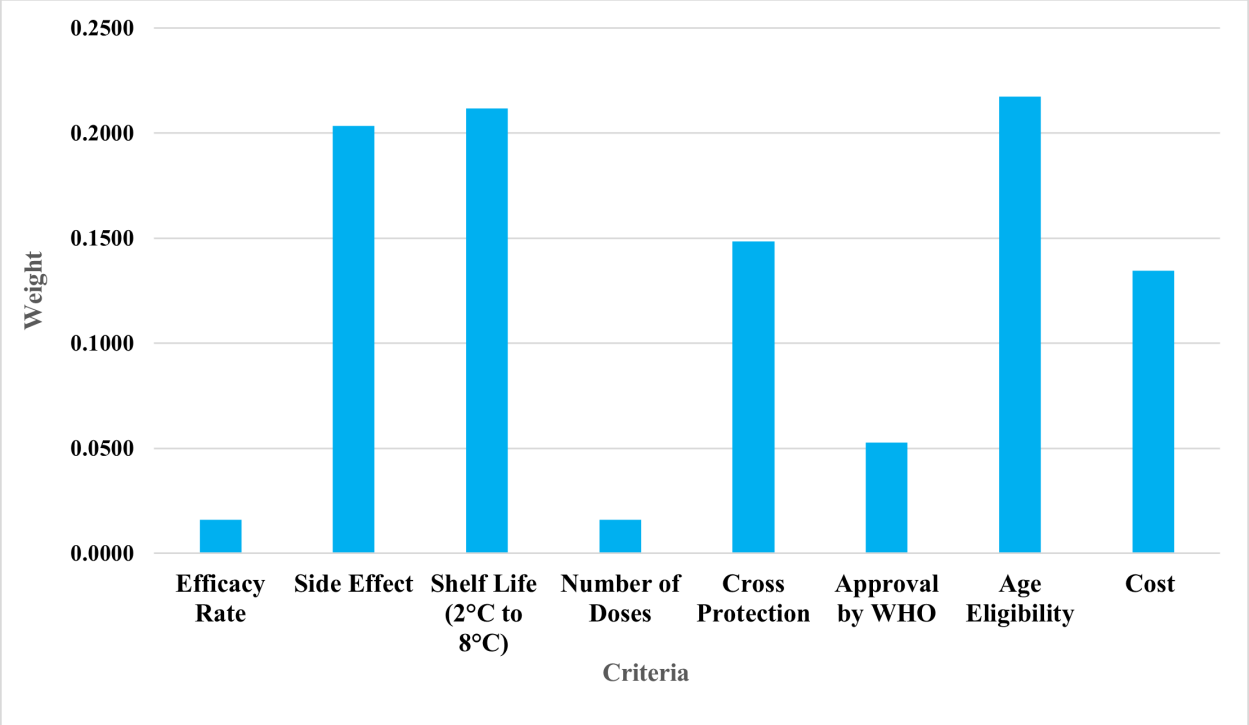
6.1.1 Interpretation of Shannon Entropy Weights

The Shannon entropy method assigns weights based on the variability of data across alternatives for each criterion. Criteria with greater variation between vaccines receive higher weights, reflecting their stronger ability to distinguish among options (Wu et al., 2011).

As illustrated in Figure 4, the calculated weights show that age eligibility, shelf life, and side effect severity are the most influential criteria. These are followed by cross-protection against variants and cost. In comparison, approval by WHO receives a low-to-moderate weight, while the efficacy rate and the number of doses receive relatively low weights.

Figure 4

Shannon Entropy Criteria Weights



These results lead to two main observations:

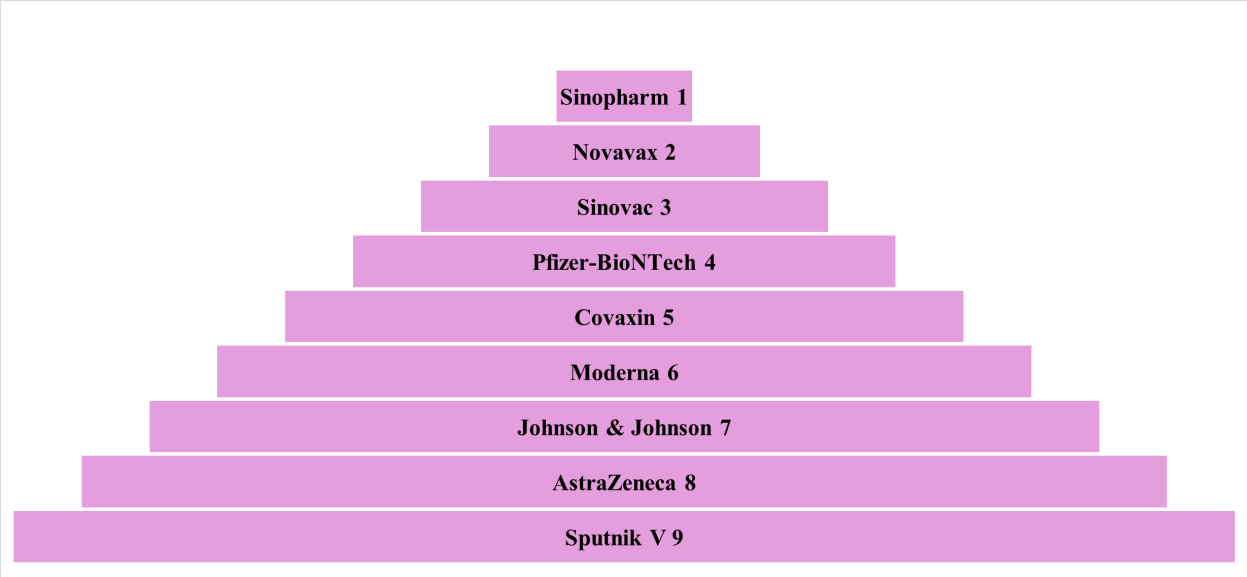
1. **Low Statistical Weight on Clinical Efficacy:** The low weight assigned to efficacy rate in this model reflects the limited variability in efficacy values across vaccines, as most alternatives show relatively high efficacy. This limited variability reduces the contribution of efficacy to differentiation within the Shannon framework, even though efficacy is substantively important in vaccine evaluation.

2. **Emphasis on Logistics and Demographic Coverage:** The top three weighted criteria, age eligibility, shelf life, and side effect severity, are closely related to logistics, feasibility, and population coverage rather than purely clinical performance. This indicates that, in this dataset, the variability in logistics- and safety-related criteria among vaccines is greater than the variability observed in their efficacy.

6.1.2 Interpretation of TOPSIS Rankings

The integration of these weights into the TOPSIS model produced the rankings shown in Figure 5.

Figure 5
Vaccine Rankings by Shannon Entropy-Weighted TOPSIS



Top-Ranked Alternatives:

Sinopharm ranks highest, mainly due to its long shelf life, mild side effects, approval by WHO, and broad age eligibility. Its moderate efficacy and cross-protection scores have less impact in this setting because these criteria receive relatively low weights.

Novavax ranks second, supported by its cross-protection performance, mild side effects, approval by WHO, broad age eligibility, and above-average shelf life. Although its storage characteristics are less favorable than those of Sinopharm, its overall profile aligns well with the weighted criteria.

Sinovac ranks third, mainly due to its very comparable logistical advantages to Sinopharm, despite having the lowest efficacy rate among the vaccines considered.

Middle-Ranked Alternatives:

Pfizer-BioNTech and **Moderna** rank 4th and 6th, respectively, despite their high efficacy and

strong cross-protection. Their shorter shelf lives and higher side effect scores lower their relative performance under this weighting structure. **Covaxin** has mild side effects and a reasonable shelf life, but its lower cross-protection reduces its overall score relative to higher-ranked alternatives.

Lower-Ranked Alternatives:

Johnson & Johnson ranks 7th, despite its one-dose regimen, because of severe side effects and moderate efficacy under the chosen metrics. **AstraZeneca**, which ranks 8th, is similarly affected by severe side effects, moderate efficacy, and moderate cross-protection, even though it is cost-effective and approved by the WHO. **Sputnik V** ranks last, despite its high efficacy, primarily due to the lack of WHO approval, severe side effects, and average performance on logistics-related criteria.

6.1.3 Thematic Insights

Influence of Logistics-Related Criteria: The relatively high weights assigned to shelf life, age eligibility, and side effect severity lead to higher rankings for vaccines that are easier to store at standard temperatures, associated with milder side effects, and authorized for broader age groups. This helps explain the high rankings of Sinopharm and Sinovac, which are widely deployed in low- and middle-income settings and have characteristics that align with these criteria (WHO, 2022).

Limited Contribution of Efficacy: Although clinical efficacy is central to vaccine assessment, the small variation in efficacy among the selected vaccines reduces its impact on rankings when weights are derived purely from Shannon entropy method. If decision-makers see these rankings as the best overall vaccine without realizing that efficacy has little influence on the final scores, they would misinterpret the findings.

6.2 Interpretation of Wen Entropy Weights and Rankings

After examining the patterns generated using Shannon entropy, the discussion turns to the Wen entropy method. This method is designed to avoid concentrating weight primarily on criteria with high variability. Instead, it promotes a more even distribution of importance across criteria, which

can lead to different results in the TOPSIS ranking (Chiang & Hsieh, 2009).

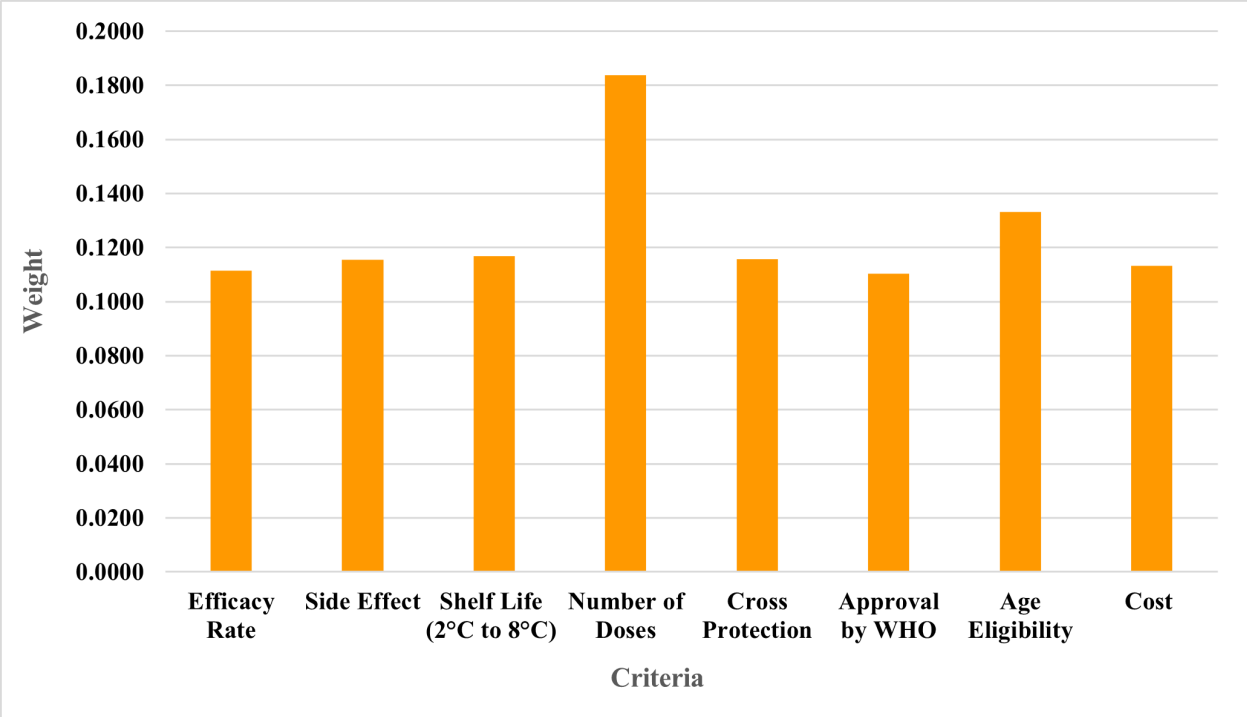
6.2.1 Interpretation of Wen Entropy Weights

Wen entropy also produces objective weights, but uses a non-linear mapping function that prevents assigning disproportionately high weights to dispersed criteria. As a result, its weighting structure tends to be more balanced, ensuring that criteria with lower dispersion but substantial practical relevance are still represented meaningfully in the model.

As shown in Figure 6, the number of doses is the most influential criterion, followed by age eligibility. The remaining criteria, efficacy rate, side effect severity, shelf life, cross-protection, approval by WHO, and cost, receive nearly uniform weights. This distribution illustrates a balanced approach that incorporates both clinical considerations and operational feasibility.

Figure 6

Wen Entropy Criteria Weights



These results lead to two main observations:

1. **Balanced Weight Distribution:** In contrast to Shannon entropy, the Wen method allocates the importance of criteria more uniformly, making sure that factors like efficacy or cross-protection influence the results even if they show a very small variation.

2. **Emphasis on Dose Regimen:** The relatively high weight assigned to the number of doses reflects the importance of operational efficiency in vaccine rollout. A single-dose schedule can reduce logistical demands and accelerate population coverage, which is especially important in time-sensitive contexts (Sadoff et al., 2021).

6.2.2 Interpretation of TOPSIS Rankings

Applying Wen entropy weights to the TOPSIS model produces the rankings shown in Figure 7, which are different in several ways from the results obtained using Shannon entropy.

Figure 7
Vaccine Rankings by Wen Entropy-Weighted TOPSIS

Top-Ranked Alternatives:

Sinopharm ranks first, supported by its long shelf life, mild side effects, approval by WHO, and broad age eligibility. Although its efficacy and cross-protection scores are moderate, the balanced

weighting structure gives its logistical advantages strong influence.

Novavax ranks second, benefiting from strong efficacy, favorable cross-protection, mild side effects, approval by WHO, broad age eligibility, and a reasonable shelf life. Because Wen entropy gives more balanced attention to all criteria, Novavax's clinical performance has greater influence than under the Shannon method.

Pfizer-BioNTech rises to third place due to its strong efficacy, high cross-protection, and broad age eligibility. Its short shelf life and moderate side effects limit its score but do not outweigh its clinical strengths under this weighting structure.

Middle-Ranked Alternatives:

Johnson & Johnson ranks fourth, benefiting from its single-dose regimen, the criterion with the highest weight. Its moderate efficacy and severe side effects prevent it from moving higher. **Moderna** ranks fifth, supported by high efficacy, broad age eligibility, and strong cross-protection, but its short shelf life and moderate side effects reduce its advantage. **Covaxin**, in sixth place, has mild side effects and a reasonable shelf life, but lower efficacy and limited cross-protection restrict its performance.

Lower-Ranked Alternatives:

Sinovac ranks seventh, as its lower efficacy receives more relative weight in this method than under Shannon entropy. **AstraZeneca**, ranked eighth, is affected by its moderate efficacy, severe side effects, and moderate cross-protection, despite its low cost. **Sputnik V** ranks last due to the combination of severe side effects, lack of WHO approval, and average logistics-related characteristics, which outweigh its high efficacy under Wen's balanced weighting method.

6.2.3 Thematic Insights

Balanced Clinical and Logistical Considerations: More even weight distribution of Wen entropy prevents any domination of single operation or demographic factor. As a result, vaccines with strong clinical performance, such as Pfizer-BioNTech receive rankings that better reflect both clinical and

logistical criteria.

Influence of Dose Regimen on Coverage Speed: The high weight assigned to the number of doses elevates vaccines like Johnson & Johnson, which reflects how single-dose vaccines can support rapid immunization strategies, especially in emergency situations.

Greater Representation of High-Efficacy Vaccines: Because Wen entropy avoids undervaluing criteria with low dispersion, high-efficacy vaccines and those with strong cross-protection gain more influence compared to the Shannon method. This balanced distribution of weights reduces the gap between clinically strong vaccines and those with logistics advantages.

6.2.4 Comparative Outcomes of Shannon and Wen Entropy

While the individual results of each method provide valuable insights, comparing them side by side highlights their methodological biases and practical implications (Table 18).

Table 18

Comparison of Shannon and Wen Entropy Outcomes

Method	Top 3 Vaccines	Key Drivers	Biggest Loser	Weight Bias
Shannon Entropy	Sinopharm, Novavax, Sinovac	High dispersion in logistics criteria (Shelf Life, Age Eligibility, Side Effects)	Pfizer-BioNTech (drops despite high efficacy)	Strong bias toward criteria with high variability; logistics over clinical efficacy
Wen Entropy	Sinopharm, Novavax, Pfizer-BioNTech	Balanced weight spread; emphasis on Number of Doses and clinical metrics	Sinovac (penalized for low efficacy)	Moderates bias; retains weight on clinically important but low-variance factors

This comparison shows that Shannon entropy tends to favor highly variable criteria while Wen entropy reduces this bias by giving greater weight to clinically important but less variable criteria.

6.3 Interpretation of Hybrid Entropy Weights and Sensitivity Analysis

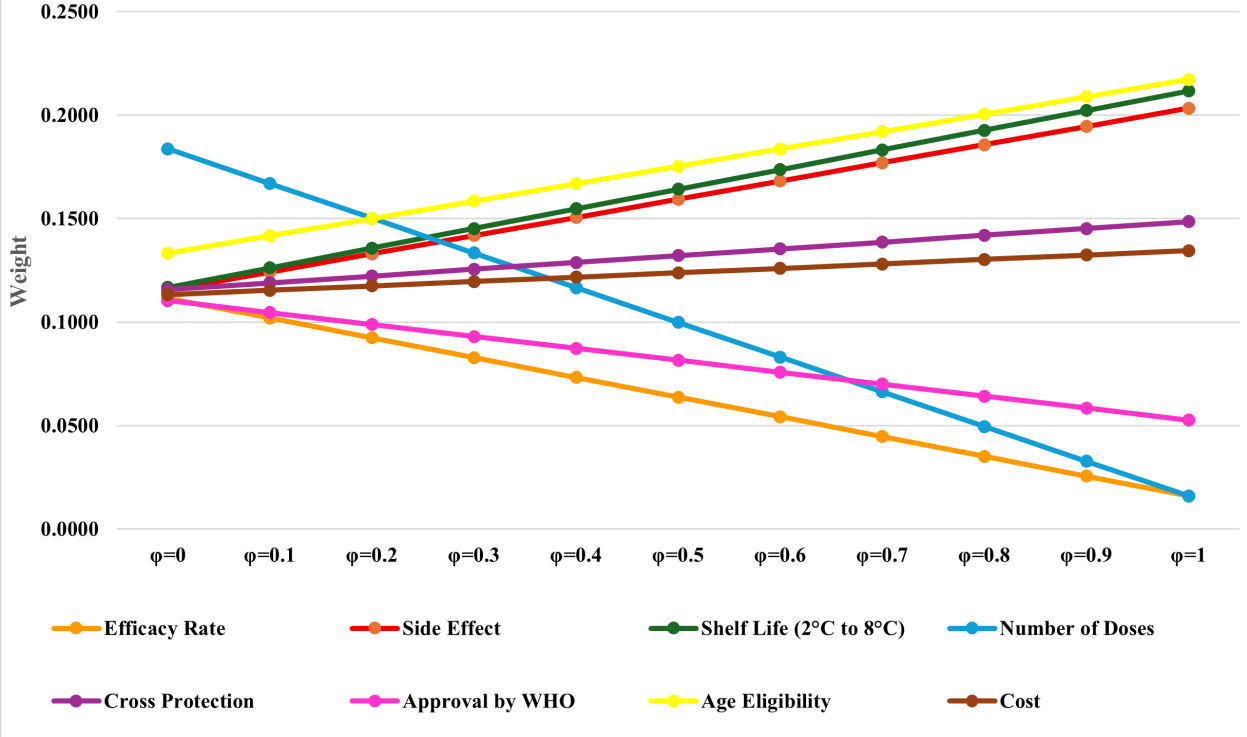
Following the individual evaluations of Shannon and Wen entropy, the analysis now turns to a hybrid approach that integrates both methods. This combined model offers greater flexibility by allowing decision-makers to adjust the balance between a more even weight distribution (Wen) and a variability-sensitive distribution (Shannon). The method achieves this flexibility through the parameter ϕ, which ranges from 0 (pure Wen entropy) to 1 (pure Shannon entropy). Varying ϕ enables decision-makers to reflect different policy priorities and examine how these shifts influence vaccine rankings.

6.3.1 Weight Evolution Across ϕ Values

The change in weights across ϕ values (Figure 8) shows a clear and continuous shift in emphasis:

Figure 8

Hybrid Entropy Weights Across ϕ Values



1. Efficacy rate and number of doses receive their highest weights at $\phi = 0$ and decline steadily

as ϕ increases, reflecting Wen entropy's stronger emphasis on clinical and dosing-related criteria. At $\phi = 1$, the two criterion weights are considerably lowered, consistent with the Shannon results where these criteria showed relatively low variability.

2. As ϕ increases, the importance of side effect severity, shelf life, and age eligibility increases consistently. For instance, age eligibility increases from 0.1333 at $\phi = 0$ to 0.2173 at $\phi = 1$. This reflects Shannon's sensitivity to variations in demographic and logistical factors.

3. Cross-protection and approval by WHO show moderate increases toward $\phi = 1$, indicating their moderate dispersion under Shannon entropy.

4. Cost shows a gradual and modest increase, indicating its relatively consistent importance across both entropy methods.

This continuous weight transition indicates the hybrid model's flexibility and its ability to shift emphasis between clinical and logistical considerations.

6.3.2 Stability and Shifts in Rankings

To assess the robustness of vaccine rankings under varying weighting schemes, a sensitivity analysis approach was used. As in Alinezhad and Amini (2011), robustness was evaluated using standard deviation and rank range, allowing identification of vaccines that maintain consistent positions across different ϕ values. A lower standard deviation indicates greater stability in response to changes in weighting preferences. Table 19 summarizes these results.

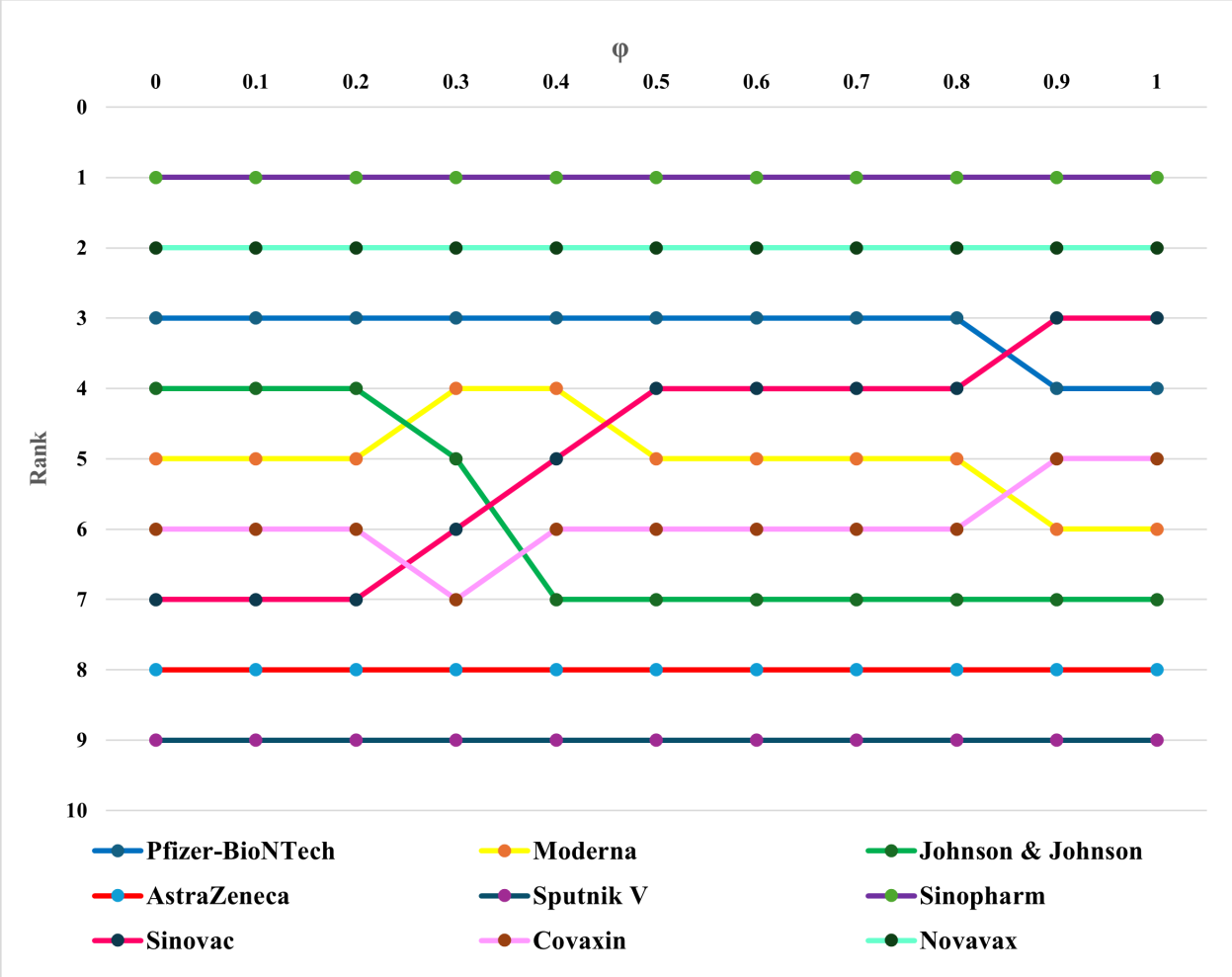
Table 19
Robustness Summary of Vaccine Rankings Across ϕ Values

Vaccine	Average (Rank)	Standard Deviation (Rank)	Rank Range	Best Rank	Worst Rank	Typology
Sinopharm	1.000	0.000	0	1	1	Universally Optimal
Novavax	2.000	0.000	0	2	2	Universally Optimal
Pfizer-BioNTech	3.182	0.386	1	3	4	Stable High Performer
Sinovac	4.909	1.505	4	3	7	Highly Sensitive
Moderna	5.000	0.603	2	4	6	Moderately Sensitive
Covaxin	5.909	0.514	2	5	7	Moderately Sensitive
J & J	6.000	1.348	3	4	7	Highly Sensitive
AstraZeneca	8.000	0.000	0	8	8	Stable but Underperformer
Sputnik V	9.000	0.000	0	9	9	Stable but Underperformer

To complement the statistical summary in Table 19 , Figure 9 visualizes how rankings evolve across the ϕ range. This figure illustrates where ranking shifts occur and highlights patterns of stability, sensitivity, and crossover behavior.

Figure 9

Vaccine Rankings Across ϕ Values



Highly Stable Positions:

Sinopharm ranks first across all ϕ values, supported by its strong logistical characteristics. **Novavax** consistently ranks second, reflecting a strong balance between clinical and logistical performance. **AstraZeneca** and **Sputnik V** remain in the lowest positions across all settings.

Moderately Stable Positions:

Pfizer-BioNTech holds third place for most ϕ values until $\phi = 0.8$, then shifts to fourth under Shannon-dominant weights. **Moderna** fluctuates between 4th and 6th depending on the weighting emphasis. **Covaxin** remains in the mid-range but shows some improvement as ϕ increases.

Highly Sensitive Positions:

Sinovac shows substantial improvement, moving from 7th to 3rd as ϕ increases. **Johnson & Johnson** begins in fourth place under Wen-dominant weights but declines as ϕ increases, stabilizing at seventh from $\phi = 0.4$ onward.

Transition Zone:

The range $\phi \in [0.3, 0.5]$ is a transition zone where several ranking changes occur. For instance, **Sinovac** rises from 6th to 5th, **Moderna** shows a temporary improvement, and **Johnson & Johnson** declines. When priorities are uncertain, results on both sides of this interval are informative.

Heatmap: To further illustrate the patterns across ϕ values, Table 20 presents a heatmap where green indicates higher rankings (better performance) and red indicates lower rankings (worse performance).

Table 20
Heatmap of Vaccine Rankings Across ϕ Values

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Pfizer-BioNTech	3	3	3	3	3	3	3	3	3	4	4
Moderna	5	5	5	4	4	5	5	5	5	6	6
Johnson & Johnson	4	4	4	5	7	7	7	7	7	7	7
AstraZeneca	8	8	8	8	8	8	8	8	8	8	8
Sputnik V	9	9	9	9	9	9	9	9	9	9	9
Sinopharm	1	1	1	1	1	1	1	1	1	1	1
Sinovac	7	7	7	6	5	4	4	4	4	3	3
Covaxin	6	6	6	7	6	6	6	6	6	5	5
Novavax	2	2	2	2	2	2	2	2	2	2	2

Stable performers such as Sinopharm and Novavax show consistent colors all over the ϕ, while highly sensitive vaccines like Sinovac and Johnson & Johnson show substantial changes in response to different weighting schemes.

6.3.3 Thematic Insights from Sensitivity Analysis

Stable Top and Bottom Performers: Sinopharm and Novavax maintain top positions across all scenarios, which show their strong overall profiles. AstraZeneca and Sputnik V are consistently at the bottom of the list due to a combination of lower clinical and logistical advantages.

Trade-Off Between Clinical and Logistical Priorities: At low ϕ values (Wen-dominant), emphasis is placed on clinical and dosing factors, benefiting vaccines with higher efficacy or single-dose schedules. At high ϕ values (Shannon-dominant), logistical characteristics become more influential, improving the rankings of vaccines with longer shelf lives or broad age eligibility.

Policy Implications: For low-resource settings, ϕ values closer to 1 may be more appropriate, as they prioritize logistical feasibility, storage stability, and broad demographic reach. For high-resource or high-risk settings, ϕ values closer to 0 may be preferred, reflecting a greater focus on clinical effectiveness and operational efficiency.

Using Sensitivity as a Guide for Decision-Making: The ϕ parameter in hybrid model acts as an adjustable control for shifting priorities. This flexibility is especially beneficial in settings where pandemic conditions evolve and vaccine availability shifts.

6.4 Scenario-Specific Recommendations

The results from the Shannon entropy, Wen entropy, and hybrid weighting analyses show that no single vaccine is the best in all situations. To translate these analytical findings into practical recommendations, the following scenario-specific guidance aligns each weighting approach with strategic public health contexts. This helps decision-makers customize the weighting scheme according to their priorities, such as rapid rollout, equity, cost efficiency, or long-term sustainability.

Scenario 1: Rural/Low-Resource rollout with Limited Cold Chain Capacity

In rural or low-resource environments, particularly in low- and middle-income countries (LMICs), vaccine selection is mainly influenced by logistical constraints rather than marginal differences in

clinical efficacy. Challenges such as limited or unreliable cold-chain systems, infrequent resupply cycles, and the difficulty of reaching remote populations make storage stability, age eligibility, and affordability especially important (Fisher et al., 2021).

For this context, the hybrid entropy parameter ϕ should be set between 0.8 and 1.0, which shifts the weighting scheme toward logistical and demographic criteria. With a high-ϕ setting, the model emphasizes shelf life, mild side effects, wide age eligibility, and lower cost, which are factors that support broad and reliable coverage in areas with limited infrastructures. Under these conditions, small differences in efficacy become less influential, as vaccines with strong logistical advantages can achieve higher coverage and impact.

The TOPSIS rankings at high ϕ values identify Sinopharm, Sinovac, and Novavax as the most suitable candidates:

- **Sinopharm** ranks highest due to its long shelf life at standard refrigeration temperatures, mild side-effect profile, WHO approval, and suitability for adults across a wide range of ages.
- **Sinovac** performs well for similar reasons: strong cold-chain compatibility, mild side effects, and broad age eligibility, despite its lower efficacy rate.
- **Novavax** adds strong clinical effectiveness to favorable logistical features such as stable storage, mild side effects, WHO approval, and availability for multiple age groups.

These results are consistent with global vaccination program experience, where Sinopharm and Sinovac have been widely used in Africa, Latin America, and parts of Asia largely because of their ease of storage and distribution (WHO, 2022). Novavax's protein subunit platform also makes it suitable for settings with limited cold-chain capacity (Anez et al., 2025).

From a policy standpoint, a high-ϕ configuration provides a weighting structure that reflects the operational realities of rural or resource-constrained settings. It highlights the importance of balancing clinical performance with logistical feasibility and equitable access, helping health authorities avoid overemphasizing small differences in efficacy at the expense of practical implementation.

Scenario 2: Sudden Outbreak / New Variant Spread (Maximize Protection)

In the event of a sudden COVID-19 outbreak or the emergence of a highly transmissible variant, the primary objective is to maximize clinical protection as quickly as possible. This places emphasis on achieving the highest available effectiveness against infection and severe disease, along with strong cross-protection against circulating and emerging variants. It is also important to minimize the number of doses required for full immunization, as this supports faster rollout and helps accelerate coverage during critical periods.

In this context, the hybrid entropy parameter ϕ should be set between 0.0 and 0.2, which increases the weight placed on efficacy rate, cross-protection, number of doses, and WHO approval. This low-ϕ range aligns with the Wen-entropy pattern, where clinical performance takes priority, while logistical and cost-related criteria receive comparatively lower emphasis. Factors such as shelf life, side effects, age eligibility, and cost remain part of the evaluation but carry less influence, as the main focus is to quickly reduce transmission, hospitalizations, and deaths.

While Sinopharm and Novavax continue to rank among the top candidates overall, a low-ϕ configuration also elevates several other clinically strong vaccines. At these settings, the TOPSIS results frequently place Pfizer-BioNTech and Johnson & Johnson among the leading options.

- **Pfizer-BioNTech** provides high efficacy, strong cross-protection, and WHO approval. Although its shelf life is short and it requires ultra-cold storage, these logistical factors are less influential at low ϕ values, where clinical outcomes are prioritized.

- **Johnson & Johnson**, despite having lower efficacy than the mRNA vaccines, benefits from its single-dose regimen. This characteristic is valuable during outbreak peaks when rapid coverage is essential and follow-up doses are harder to administer.

These patterns reflect responses observed during major outbreak periods in late 2021 and early 2022, when many countries relied primarily on mRNA vaccines to address the spread of Omicron and other variants, even with the additional complication of cold-chain management (Polack et al., 2020; Baden et al., 2021). Johnson & Johnson's single-dose formulation was also used in areas

where administering two-dose vaccination schemes has become increasingly challenging (Sadoff et al., 2021).

From a policy standpoint, the low-ϕ configuration illustrates the need to prioritize immediate clinical protection during periods of rapid transmission. In such situations, the benefits of higher efficacy and broader variant coverage can outweigh the convenience of logistics if short-term cold-chain capacity and emergency distribution systems are ready to be deployed.

Scenario 3: Balanced Immunization

In countries where healthcare systems include both heavily populated urban centers and moderately equipped rural areas, vaccine selection must consider both clinical performance and distribution feasibility. These conditions are common in middle-income regions with mixed infrastructure, where cold-chain capacity is available but may be limited. The objective in this scenario is to provide strong protection against COVID-19 while maintaining practical and sustainable deployment.

In this setting, the hybrid entropy parameter ϕ should be set between 0.3 and 0.6, creating a middle-ground weighting structure that considers both clinical and logistical priorities. A mid-range value moderately emphasizes efficacy rate and cross-protection to ensure resilience against variants, while also assigning meaningful importance to shelf life, side effects, and cost to support wider distribution. Approval by WHO remains relevant for establishing trust, regulatory compliance, and compatibility with national policy frameworks.

Based on the TOPSIS results under these weighting conditions, Novavax, Pfizer-BioNTech, and Sinopharm are preferred options.

- **Novavax** demonstrates strong efficacy, good cross-protection, mild side effects, and adequate shelf life, making it suitable for both urban and semi-rural deployment.

- **Pfizer-BioNTech** provides high efficacy and strong cross-protection, though its short shelf life may limit its application in rural areas. In urban regions with reliable cold-chain systems, it performs effectively.

- **Sinopharm** offers logistical advantages, including extended shelf life and mild side effects, which support distribution in rural areas and help reduce the impact of its relatively weaker clinical performance.

This prioritization reflects the challenges of coordinating immunization across environments with different infrastructure. A mid-ϕ setting supports an approach that accounts for both protection levels and deployment practicality, enabling decision-makers to serve diverse populations without requiring major trade-offs.

From a policy perspective, the balanced weighting highlights the need for vaccines suitable for a variety of distribution settings. While vaccines with high clinical effectiveness may pose logistical challenges in rural areas, those that are easier to store and transport may offer more consistent access. The vaccines identified in this scenario perform adequately across both settings, making them well suited for long-term national immunization strategies rather than short-term emergency response.

Table 21
Scenario-Specific Vaccine Recommendations

Scenario	Policy Context	ϕ Range	Top 3 Vaccines	Selection Rationale
Rural / Low-Resource rollout with Limited Cold Chain	LMICs or rural areas with limited refrigeration, long transport times, and emphasis on equitable access	0.8–1.0	Sinopharm, Sinovac, Novavax	Long shelf life, mild side effects, broad age eligibility, cost suitability; logistical attributes prioritized over clinical variability.
Sudden Outbreak / New Variant Spread (Maximize Protection)	Urban outbreaks, variant emergence, emergency response environments	0.0–0.2	Sinopharm, Novavax, Pfizer-BioNTech, Johnson & Johnson	High efficacy and cross-protection; single-dose J&J enables rapid coverage; logistics are lower priority.
Balanced Immunization	Mixed urbanrural systems with moderate cold-chain capacity and budget constraints	0.3–0.6	Novavax, Pfizer-BioNTech, Sinopharm	Balances clinical effectiveness with storage and deployment feasibility across diverse regions.

6.5 Implications for Policy

The findings from this study highlight several considerations related to vaccine policy design, particularly regarding the use of MCDM in uncertain environments.

Flexibility: Relying on a single weighting method can lead to recommendations that place disproportionate emphasis on either clinical or logistical factors, which do not reflect the ongoing changes in the pandemic. For example, a purely Shannon-based approach, when faced with low variability in efficacy data, may place greater weight on logistical differences and prioritize vaccines that are easier to store but provide weaker clinical protection. Conversely, an exclusively Wen-based

approach may overlook important supply chain and demographic considerations. The hybrid-entropy-weighted modified TOPSIS method introduced in this study supports flexible decision-making. By adjusting the parameter ϕ, decision-makers can shift the balance between clinical performance and operational feasibility as the situation changes. This adaptability is important for maintaining responsive and evidence-based policy decisions.

Equity and trust: Including WHO approval status as one of the criteria supports both operational planning and alignment with global regulatory expectations. Vaccines without WHO approval may face limitations in cross-border immunization programs, multilateral procurement mechanisms such as COVAX, or public acceptance in settings where regulatory endorsement influences trust (Sheen et al., 2023; WHO, 2021). Policymakers can reduce these risks by considering WHO approval as an essential requirement in contexts involving international collaboration, shared supply chains, or joint procurement. This approach enhances public trust and ensures compatibility with global standards and funding frameworks.

Generalizability and preparedness: Beyond the COVID-19 case study, the framework can be adapted for other vaccine selection challenges and broader allocation problems. It can support seasonal influenza vaccine decisions, where strain match, production speed, and cold-chain requirements vary annually. The same approach can be used for therapeutics (e.g., antivirals), essential supplies (e.g., oxygen, masks), and resource allocation such as ICU capacity. Incorporating such adaptable decision tools into national and international health planning can strengthen preparedness for future public health emergencies.

The hybrid-entropy-weighted modified TOPSIS framework offers a structured decision-making approach that integrates methodological rigor with practical applicability. Rather than identifying a single universally optimal vaccine, the framework supports transparent, flexible, and context-specific evaluations that can be adjusted as conditions evolve throughout a pandemic.

Chapter VII: Conclusion and Recommendations

This thesis examines one of the most complex decision-making challenges that occurred during the COVID-19 pandemic: selecting vaccines while accounting for clinical, logistical, economic, and regulatory considerations. Existing approaches, whether being economic, epidemiological, or expert-based, have often been limited by their narrow scope, subjective weighting, or limited adaptability to changing conditions (Utami et al., 2022; Sinuraya et al., 2024).

To address these limitations, this research developed and evaluated a hybrid-entropy-weighted modified TOPSIS framework. The model combines Shannon entropy, which is sensitive to the variability of the data with Wen entropy, which captures non-linearity and uncertainty. The inclusion of the parameters ϕ and λ enables decision-makers to adjust the balance between clinical performance and logistical feasibility depending on operational needs. Using empirical data from nine COVID-19 vaccines, the model was applied across multiple ϕ and λ values to produce rankings, conduct sensitivity analyses, and generate context-specific recommendations.

7.1 Key Findings

The in-depth analysis conducted in this study offers several insights regarding the use of Shannon entropy, Wen entropy, and hybrid weighting within a TOPSIS framework for vaccine evaluation. These results are summarized in four main areas:

1. Weighting patterns

- Under Shannon entropy weighting method, criteria such as age eligibility, shelf life, and side effects got the highest weights, reflecting greater variability in logistical and demographic criteria across vaccines.
- Wen entropy produced a more balanced weight distribution, with the number of doses receiving the highest weight, followed by shelf life, side effects, and age eligibility.

- The hybrid parameters ϕ and λ showed that adjusting weight focus can considerably change the rankings, offering policymakers the flexibility to tailor the decisions to specific contexts.

2. Ranking trends

- Across all combinations of ϕ and λ, Sinopharm and Novavax consistently ranked among the top alternatives as they were best in both clinical and logistical areas.
- Under low-ϕ settings, which emphasize efficacy and cross-protection, Pfizer-BioNTech and Moderna rose in rank.
- AstraZeneca and Sputnik V consistently ranked lowest across all scenarios. Although clinically effective, both exhibited severe side effects, and Sputnik V lacked WHO approval, which contributed to its consistently lower position.

3. Scenario-specific suitability

- **Low ϕ (0.0–0.2):** Suitable for sudden outbreaks or new variant waves, where clinical protection is prioritized (Novavax, Pfizer-BioNTech, Johnson & Johnson).
- **Mid ϕ (0.3–0.6):** Suitable for balanced immunization strategies where both clinical and logistical factors matter (Novavax, Pfizer-BioNTech, Sinopharm).
- **High ϕ (0.8–1.0):** Suitable for rural or low-resource settings with limited cold-chain capacity, where logistical feasibility and safety are prioritized (Sinopharm, Sinovac, Novavax).

4. Policy alignment

- Flexibility in weighting structures allows policymakers to update vaccine priorities without changing the decision framework.
- Considering WHO approval as a must can support regulatory alignment, improve public trust, and facilitate participation in global procurement systems.

- The framework is adaptable to other vaccine programs and resource allocation decisions, improving preparedness for future health crises.

Overall, the evaluation of vaccines in different settings shows that no vaccine is perfect for all scenarios. However, adjusting ϕ and λ allows decision-makers to align rankings with specific operational objectives and public health priorities.

7.2 Theoretical Contributions

This research makes several important contributions to the theoretical development of MCDM models, particularly within the context of public health emergency decision-making. The proposed approach strengthens the applicability, flexibility, and reliability of existing models while addressing limitations identified in earlier studies.

7.2.1 Integration of Dual-Entropy Weighting

By combining both entropy-based approaches, this thesis shows that it is possible to retain the objectivity of variability-based weighting while reducing the risk of underestimating the importance of criteria with low variance but high clinical relevance. This methodological contribution is applicable to a wide range of decision contexts where the importance of criteria is shaped by data distribution and situational priorities.

7.2.2 Application of the Adjustable Hybrid Parameters (ϕ and λ)

A central contribution of this work is the use of the parameters ϕ and λ, which enable a continuous transition between Shannon and Wen entropy weighting approaches.

- These parameters transform the weighting procedure from a fixed calculation into a dynamic and adaptable decision-support mechanism.
- They allow decision-makers to adjust the balance between clinical performance and logistical feasibility directly, based on operational needs.

- The model accommodates scenario-specific configurations, supporting applications ranging from outbreak response to balanced immunization strategies and equity-focused distribution plans.

7.2.3 Extension of TOPSIS for Vaccine Selection

Although TOPSIS is widely used for ranking alternatives based on proximity to an ideal solution, its use in pandemic vaccine evaluation has been limited by fixed weighting assumptions. This thesis enhances the TOPSIS method by:

- Incorporating dual-entropy hybrid weighting to reflect both objective variability and contextual priorities,
- Embedding scenario analysis through the explicit link between ϕ, λ, and real-world operational considerations,
- Demonstrating how the approach can be scaled to other public health applications beyond COVID-19 vaccines.

In summary, the model contributes to the MCDM literature by showing how a traditionally static method can be adapted into a dynamic decision-support framework while maintaining analytical rigor. It advances theoretical development by moving beyond uniform weighting assumptions and introducing an adaptive, context-sensitive approach to complex health decisions.

7.3 Practical Implications

The proposed framework offers a practical decision-support tool for large-scale health interventions, specifically for policymakers, public health authorities, and other stakeholders. It is valuable mainly because of its adaptability, transparency, and applicability across diverse public health contexts.

7.3.1 Adaptability to Evolving Conditions

The introduction of the hybrid parameters (ϕ, λ) allows vaccine prioritization to adapt to evolving public health needs. These parameters enable dynamic adjustment between clinical strength and logistical feasibility without redesigning the decision model. This flexibility is valuable during events such as emerging variants, supply chain changes, or shifts in public acceptance. By adjusting ϕ and λ, vaccine strategies can remain aligned with operational constraints and epidemiological developments.

7.3.2 Transparency and Accountability

Public confidence in vaccine selection and distribution is closely linked to the transparency and accountability of the institutions (Roy et al., 2022). By providing clear and reproducible steps for weighting, normalization, and ranking using both Excel and Python, the framework is able to support such principles. Its structure allows for tracing how each criterion contributes to the final ranking and how adjustments to ϕ and λ influence outcomes. This clarity helps decision-makers communicate trade-offs more effectively and enhances public understanding and acceptance.

7.3.3 Transferability to Other Health Interventions

Although initially designed for COVID-19 vaccine evaluation, the framework is versatile and can be applied to a wide range of health decisions. It can support:

- Allocation of antiviral medicines by assessing efficacy, storage requirements, shelf life, and costs,
- Seasonal vaccination programs such as influenza or HPV, where logistics and coverage objectives vary,
- Other medical resource allocation problems, including distribution of personal protective equipment, oxygen supplies, or critical-care resources.

The model's adaptable and variable criteria framework not only supports the integration of new metrics but also preserves the integrity of the overall decision-making process, thus making it more practical.

7.3.4 Strategic Planning Applications

Beyond immediate operational decisions, the model supports long-term planning. Governments and public health agencies can explore different ϕ and λ scenarios to identify potential gaps in infrastructure, regulatory processes, or resource allocation. It can also be used as a training tool for emergency preparedness exercises or as a standardized methodology for multinational collaborations in procurement and distribution strategies.

Therefore, the model provides a versatile, transparent, and context-sensitive foundation for decision-making. Its adaptability enables it to respond to changing epidemiological and logistical conditions, while its transparency supports trust and accountability. Its transferability further enhances its value for a wide range of public health applications. Together, these characteristics make the framework a useful bridge between methodological development in MCDM and practical implementation in health policy.

7.4 Limitations and Future Works

While the proposed model demonstrates strong methodological robustness and adaptability, several limitations remain. Acknowledging these limitations is essential for interpreting the results accurately and for guiding future improvements.

One key limitation is data dependency. The model's reliability, as discussed in the data collection chapter, is highly dependent on the accuracy, completeness, and timeliness of its input data. During the COVID-19 pandemic, reported values for vaccine efficacy, side effects, and cross-protection varied widely in different studies and were revised whenever new evidence came in. However, information related to shelf life, storage requirements, and real-world effectiveness often lagged behind emerging research (Manheim et al., 2016). Furthermore, variations in reporting

standards across countries and agencies created challenges in comparing and integrating data reliably (Fairchild et al., 2018). These constraints highlight the importance of recognizing and, where possible, mitigating the effects of inconsistent or evolving data.

Another limitation is that the model represents a static snapshot of the decision environment. Once the decision matrix and weights are established, the model does not automatically incorporate new evidence or update its normalization and weighting calculations. Changes in variant prevalence, booster recommendations, or WHO approvals require manual updates to the inputs. As a result, there is a risk that policy recommendations may lag behind rapid epidemiological or regulatory developments.

Finally, although the model provides a structured and quantitative approach for evaluating COVID-19 vaccines, it simplifies the complex public health decisions into numerical rankings. Even the sensitivity analysis, involving the exploration of how changes in criteria weights affect outcomes, cannot always allow the resulting recommendations to be nuanced enough to reflect the real-world decision-making context. Thus, the framework should be considered a decision-support tool rather than a definitive solution.

Future work should focus on addressing these limitations. Incorporating real-time epidemiological data, such as variant prevalence, infection rates, and vaccination coverage, would enhance the model's ability to adapt to changing conditions. Expanding the model to include additional entropy variants would further increase its flexibility and applicability to a wider range of MCDM problems.

Integrating the framework with other MCDM techniques, such as VIKOR, PROMETHEE, or ELECTRE, may also provide complementary perspectives, improve robustness in ranking results, and offer deeper insights for complex public health decisions. Collectively, these enhancements would strengthen the model's effectiveness as a strategic and operational decision-support tool in rapidly evolving health contexts.

7.5 Policy Recommendations

The framework developed in this study offers methodological innovation and practical value for a wide range of stakeholders. By incorporating a policy-adjustable weighting scheme (mixing control parameters ϕ and λ), decision-makers can align vaccine selection with the operational priorities and constraints of different contexts. The following sections outline how various policymakers can apply the model, what insights it provides, and the practical benefits it offers.

1. National Health Ministries

The national health authorities are responsible for planning and execution of strategic procurement, allocation and rollout not only for pandemics but also for routine immunization programs (PAHO, 2022). The ϕ and λ parameters allow these authorities to adjust vaccine selection priorities as conditions evolve. For example, during an outbreak phase, ϕ can be lowered to emphasize high-efficacy vaccines, while in steady-state phases or rural rollout campaigns, ϕ can be increased to prioritize vaccines with longer shelf lives, mild side effects, and minimal cold-chain requirements.

This capacity enables region-specific strategies rather than uniform nationwide approaches. High-performance vaccines can be deployed in urban hospitals, while logistically flexible vaccines can be allocated to rural clinics, supporting broader coverage and stronger health impact.

2. Global Health Agencies (WHO, UNICEF, Gavi)

Global health agencies such as WHO, UNICEF, and Gavi coordinate COVAX allocations, manage cross-border vaccine shipments, and oversee multi-country procurement efforts to ensure equitable access (UNICEF, 2023). The model's transparency, reproducibility, and scenario-based adaptability allow these agencies to justify allocation decisions using objective measures combined with contextual logistical considerations. These justifications help explain why certain countries receive specific vaccine mixes, especially when logistical compatibility outweighs small differences in efficacy.

The model therefore supports equitable global distribution by incorporating logistical feasibility

into allocation planning. It also enhances trust among stakeholders by providing a consistent and defensible rationale for distribution decisions.

3. Emergency Response Task Forces

Emergency response task forces operate in high-pressure environments such as variant-driven surges or outbreak hotspots. In such settings, a low-ϕ configuration prioritizes clinical performance, enabling rapid reduction of transmission and hospitalization rates. Logistical challenges become secondary considerations during these acute phases.

This weighting approach supports the rapid deployment of vaccines with strong cross-protection, even when they require more complex storage. It buys critical time to prepare and distribute more logistics-friendly vaccines once the immediate crisis is under control.

4. International Donors and Development Banks

International donors and development banks fund vaccine procurement, establish cold-chain capacity, and strengthen health systems in low- and middle-income countries (Hayman et al., 2022). Scenario simulations generated from the model highlight trade-offs between infrastructure investment and performance outcomes. For instance, the simulations can indicate whether expanding cold-chain capacity would increase access to high-performance vaccines in future outbreaks or whether existing infrastructure is sufficient to support a logistics-first strategy.

This evidence helps guide funding toward long-term system resilience rather than short-term procurement, supporting preparedness for future health emergencies.

The proposed framework connects academic modeling with the operational needs of diverse public health stakeholders. By aligning its outputs with the practical demands of national ministries, global health agencies, emergency response teams, and international donors, the model provides actionable insights tailored to each role. It also offers a unified decision-support structure that strengthens coordination across different levels of governance and ensures that vaccine selection remains data-driven, context-sensitive, and adaptable to evolving challenges.

The main conclusion of this research is that no single vaccine is optimal for all circumstances. The most appropriate choice depends on the context, an urban outbreak that requires maximum clinical protection, a rural rollout prioritizing logistical considerations, or a mixed environment requiring a balance of both. By integrating analytical rigor with adaptable policy options, the framework supports equitable and practical vaccine allocation during pandemics.

Beyond COVID-19, this adaptable, data-driven model can serve as an evidence-based decision-support tool for future health emergencies. It is designed to guide rapid, context-sensitive decisions for vaccines and other public health interventions that require balancing speed, equity, and operational efficiency.

References

Abdelwahab, S. F., Issa, U. H., & Ashour, H. M. (2021). A novel vaccine selection decision-making model (VSDMM) for COVID-19. *Vaccines, 9*(7), 718. https://doi.org/10.3390/vaccines9070718

Al Kaabi, N., Zhang, Y., Xia, S., Yang, Y., Al Qahtani, M. M., Abdulrazzaq, N., Al Nusair, M., Hassany, M., Jawad, J. S., Abdalla, J., Hussein, S. E., Al Mazrouei, S. K., Al Karam, M., Li, X., Yang, X., Wang, W., Lai, B., Chen, W., Huang, S., Wang, Q., Yang, T., Liu, Y., Ma, R., Hussain, Z. M., Khan, T., Fasihuddin, M. S., You, W., Xie, Z., Zhao, Y., Jiang, Z., Zhao, G., Zhang, Y., Mahmoud, S., ElTantawy, I., Xiao, P., Koshy, A., Zaher, W. A., Wang, H., Duan, K., Pan, A., & Yang, X. (2021). Effect of 2 inactivated SARS-CoV-2 vaccines on symptomatic COVID-19 infection in adults: a randomized clinical trial. *JAMA, 326*(1), 35–45. https://doi.org/10.1001/jama.2021.8565

Al-Jebouri, M. M., & Kaki, M. N. M. (2025). Application of Matrices Modelling for Infectious Diseases of Humans. *Open Journal of Applied Sciences, 15*(9), 2733-2758. https://doi.org/10.4236/ojapps.2025.159184

Alamer, E., Alhazmi, A., Qasir, N. A., Alamer, R., Areeshi, H., Gohal, G., Qadri, M., Hashem, A. M., & Algaissi, A. (2021). Side effects of COVID-19 Pfizer-BioNtech mRNA vaccine in children aged 12-18 years in Saudi Arabia. *Vaccines, 9*(11), 1297. https://doi.org/10.3390/vaccines9111297

Alamoodi, A. H., Zaidan, B. B., Albahri, O. S., Garfan, S., Ahmaro, I. Y. Y., Mohammed, R. T., Zaidan, A. A., Ismail, A. R., Albahri, A. S., Momani, F., Al-Samarraay, M. S., Jasim, A. N., & Malik, R. Q. (2023). Systematic review of MCDM approach applied to the medical case studies of COVID-19: Trends, bibliographic analysis, challenges, motivations, recommendations, and future directions. *Complex & Intelligent Systems, 9*(4), 47054731. https://doi.org/10.1007/s40747-023-00972-1

Alinezhad, A., & Amini, A. (2011). Sensitivity analysis of TOPSIS technique: the results of change in the weight of one attribute on the final ranking of alternatives. *Journal of Optimization in Industrial Engineering, 7*(13), 23–28.

Almulhim, T., & Barahona, I. (2023). An extended picture fuzzy multicriteria group decision analysis with different weights: A case study of COVID-19 vaccine allocation. *Socio-Economic Planning Sciences, 85*, 101435. https://doi.org/10.1016/j.seps.2022.101435

Alsalem, M. A., Alamoodi, A. H., Albahri, O. S., Dawood, K. A., Mohammed, R. T., Alnoor, A., Zaidan, A. A., Albahri, A. S., Zaidan, B. B., Jumaah, F. M., & Al-Obaidi, J. R. (2022). Multi-criteria decision-making for coronavirus disease 2019 applications: A theoretical analysis review. *Artificial Intelligence Review, 55*(6), 4979–5062. https://doi.org/10.1007/s10462-021-10124-x

Andrews, N., Stowe, J., Kirsebom, F., Toffa, S., Rickeard, T., Gallagher, E., Gower, C., Kall, M., Groves, N., O'Connell, A.-M., Simons, D., Blomquist, P. B., Zaidi, A., Nash, S., Abdul Aziz, N. I. B., Thelwall, S., Dabrera, G., Myers, R., Amirthalingam, G., Gharbia, S., Barrett, J. C., Elson, R., Ladhani, S. N., Ferguson, N., Zambon, M., Campbell, C. N. J., Brown, K., Hopkins, S., Chand, M., Ramsay, M., & Lopez Bernal, J. (2022). Covid-19 vaccine effectiveness against the Omicron (B.1.1.529) variant. *New England Journal of Medicine, 386*(16), 1532–1546. https://doi.org/10.1056/NEJMoa2119451

Anez, G., McGarry, A., Woo, W., Kotloff, K. L., Gay, C. L., Zhu, M., Cloney-Clark, S., Nelson, J., Dunbar, H., Cai, M. R., Cho, I., Cai, Z., Kalkeri, R., Plested, J. S., Patel, N., Smith, K., Marchese, A. M., Glenn, G. M., Mallory, R. M., & Dunkle, L. M. (2025). Safety and immunogenicity of four sequential doses of NVX-CoV2373 in adults and adolescents: A phase 3, randomized, placebo-controlled trial (PREVENT-19). *Vaccine, 61*, 127362. https://doi.org/10.1016/j.vaccine.2025.127362

Antioch, K. M., Kuek, A., Pilla, J., & Marshall, R. (2024). A multi-criteria decision analysis framework that prioritizes economic policy to enhance value based health care during the COVID-19 pandemic. *Discover Health Systems, 3*(1), 12. https://doi.org/10.1007/s44250-024-00070-0

Appadoo, S. S., Bhatt, S. K., & Bector, C. R. (2012). A mixed solution strategy for group multi-attribute TOPSIS model with application to supplier selection problem. *Journal of Information and Optimization Sciences, 33*(1), 13–40. https://doi.org/10.1080/02522667.2012.10700132

Ariyarajah, A., Berry, I., Haldane, V., Loutet, M., Salamanca-Buentello, F., & Upshur, R. E. (2022). Identifying priority challenges and solutions for COVID-19 vaccine delivery in low- and middle-income countries: A modified Delphi study. *PLoS Global Public Health, 2*(9), e0000844. https://doi.org/10.1371/journal.pgph.0000844

Arnold, C. (2020). The biggest logistics challenge in history. *New Scientist, 248*(3309), 36-40. https://doi.org/10.1016/S0262-4079(20)32048-0

AstraZeneca Inc. (2021). *AstraZeneca COVID-19 vaccine (AZD1222) product monograph* [Product monograph]. Retrieved July 5, 2025, from https://pdf.hres.ca/dpd_pm/00062193.PDF

Babamahmoodi, F., Saeedi, M., Alizadeh-Navaei, R., Hedayatizadeh-Omran, A., Mousavi, S. A., Ovaise, G., Kordi, S., Akbari, Z., Azordeh, M., Ahangarkani, F., & Alikhani, A. (2021). Side effects and immunogenicity following administration of the Sputnik V COVID-19 vaccine in health care workers in Iran. *Scientific Reports, 11*(1), 21464. https://doi.org/10.1038/s41598-021-00963-7

Baden, L. R., El Sahly, H. M., Essink, B., Kotloff, K., Frey, S., Novak, R., Diemert, D., Spector, S. A., Rouphael, N., Creech, C. B., McGettigan, J., Khetan, S., Segall, N., Solis, J., Brosz, A., Fierro, C., Schwartz, H., Neuzil, K., Corey, L., Gilbert, P., Janes, H., Follmann, D., Marovich,

M., Mascola, J., Polakowski, L., Ledgerwood, J., Graham, B. S., Bennett, H., Pajon, R., Knightly, C., Leav, B., Deng, W., Zhou, H., Han, S., Ivarsson, M., Miller, J., & Zaks, T. (2021). Efficacy and safety of the mRNA-1273 SARS-CoV-2 vaccine. *New England Journal of Medicine, 384*(5), 403–416. https://doi.org/10.1056/NEJMoa2035389

Baier, T., & Neuwirth, E. (2007). Excel::Com. *Computational Statistics, 22*(1), 91–108. https://doi.org/10.1007/s00180-007-0023-6

Bartsch, Y. C., Chen, J. W., Kang, J., Burns, M. D., St Denis, K. J., Sheehan, M. L., Davis, J. P., Edlow, A. G., Balazs, A. B., Yonker, L. M., & Alter, G. (2022). BNT162b2 induces robust cross-variant SARS-CoV-2 immunity in children. *npj Vaccines, 7*(1), 158. https://doi.org/10.1038/s41541-022-00575-w

Bazrafshan, H., Jahromi, L. S. M., Parvin, R., & Ashraf, A. (2022). A case of Guillain-Barre syndrome after the second dose of AstraZeneca COVID-19 vaccination. *Turkish Journal of Physical Medicine and Rehabilitation, 68*(2), 295. https://doi.org/10.5606/tftrd.2022.9984

Behzadian, M., Otaghsara, S. K., Yazdani, M., & Ignatius, J. (2012). A state-of-the-art survey of TOPSIS applications. *Expert Systems with Applications, 39*(17), 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056

Belayachi, J., Mhayi, A., Majidi, H., El Fahime, E., & Abouqal, R. (2024). Effectiveness of Sinopharm's BBIBP-CorV booster vaccination against COVID-19-related severe and critical cases and deaths in Morocco during the Omicron wave. *Vaccines, 12*(3), 244. https://doi.org/10.3390/vaccines12030244

Bharat Biotech International Limited. (2021, July 3). *Final analysis of Phase 3 clinical trials of COVAXIN® (BBV152): Safety and efficacy data* [PDF]. Retrieved July 5, 2025, from https://www.bharatbiotech.com/images/press/

barat-biotech-bbv152-covaxin-phase3-final-analysis-03July2021.pdf

Bharat Biotech International Limited. (2022, January 12). *COVAXIN® (BBV152) booster shown to neutralize both Omicron and Delta variants of SARS-CoV-2* [Press release]. Retrieved July 5, 2025, from https://www.bharatbiotech.com/images/press/covaxin-neutralize-delta-and-omicron-variants-press-release.pdf

Bhiman, J. N., Richardson, S. I., Lambson, B. E., Kgagudi, P., Mzindle, N., Kaldine, H., Crowther, C., Gray, G., Bekker, L.-G., Novavax Trial Clinical Lead Author Group, Shinde, V., Bennett, C., Glenn, G. M., Madhi, S. A., & Moore, P. L. (2023). Novavax NVX-COV2373 triggers neutralization of Omicron sub-lineages. *Scientific Reports, 13*(1), 1222. https://doi.org/10.1038/s41598-023-27698-x

Bian, L., Liu, J., Gao, F., Gao, Q., He, Q., Mao, Q., Wu, X., Xu, M., & Liang, Z. (2022). Research progress on vaccine efficacy against SARS-CoV-2 variants of concern. *Human Vaccines & Immunotherapeutics, 18*(5), 2057161. https://doi.org/10.1080/21645515.2022.2057161

Blasioli, E., Mansouri, B., Tamvada, S. S., & Hassini, E. (2023, March). Vaccine allocation and distribution: A review with a focus on quantitative methodologies and application to equity, hesitancy, and COVID-19 pandemic. In *Operations Research Forum* (Vol. 4, No. 2, p. 27). Cham: Springer International Publishing. https://doi.org/10.1007/s43069-023-00194-8

Brans, J. P., & Vincke, P. (1985). Note—A preference ranking organisation method: (The PROMETHEE method for multiple criteria decision-making). *Management Science, 31*(6), 647656. http://dx.doi.org/10.1287/mnsc.31.6.647

Centers for Disease Control and Prevention. (2024). *Pfizer-BioNTech COVID-19 vac-*

cine: Summary for healthcare providers [Web page]. Retrieved July 5, 2025, from https://www.cdc.gov/vaccines/php/info-by-product/pfizer-covid-19-summary.html

Centers for Disease Control and Prevention. (2024). *20242025 formula Pfizer-BioNTech COVID-19 vaccine: Standing orders for administering vaccine (6 months through 4 years of age, CS321570 AO)* [Standing orders]. Retrieved July 5, 2025, from https://www.cdc.gov/vaccines/covid-19/info-by-product/pfizer/downloads/infant-standing-orders.pdf

Centers for Disease Control and Prevention. (2025). *Coronavirus disease 2019 (COVID-19) vaccine safety* [Web page]. Retrieved July 5, 2025, from https://www.cdc.gov/vaccine-safety/vaccines/covid-19.html

Centers for Disease Control and Prevention. (2023). *Moderna COVID 19 vaccine summary* [Product summary]. Retrieved July 5, 2025, from https://www.cdc.gov/vaccines/php/info-by-product/moderna-covid-19-summary.html

Centers for Disease Control and Prevention. (2024). *Standing orders for administering Moderna COVID-19 vaccine for children 5 years and older* [Standing orders]. Retrieved July 5, 2025, from https://www.cdc.gov/vaccines/covid-19/info-by-product/moderna/downloads/standing-orders-5yrs-older-508.pdf

Centers for Disease Control and Prevention. (2024). *GRADE: Moderna COVID19 vaccine for children aged 6 months–5 years* [Web page]. Retrieved July 5, 2025, from https://www.cdc.gov/acip/grade/covid-19-moderna-vaccine-6-months-5-years.html

Centers for Disease Control and Prevention. (2022). *Novavax COVID-19 vaccine reactogenicity* [Web page]. Retrieved July 5, 2025, from https://archive.cdc.

gov/www_cdc_gov/vaccines/covid-19/info-by-product/novavax/reactogenicity.html

Centers for Disease Control and Prevention. (2023). *Novavax COVID-19 vaccine (monovalent): Standing orders for administering vaccine to persons 12 years of age and older* [Standing orders]. Retrieved July 6, 2025, from https://stacks.cdc.gov/view/cdc/129920

Chen, C. H. (2021). A hybrid multi-criteria decision-making approach based on ANP-entropy TOPSIS for building materials supplier selection. *Entropy, 23*(12), 1597. https://doi.org/10.3390/e23121597

Chiang, Y. M., & Hsieh, H. H. (2009). The use of the Taguchi method with grey relational analysis to optimize the thin-film sputtering process with multiple quality characteristic in color filter manufacturing. *Computers & Industrial Engineering, 56*(2), 648–661. https://doi.org/10.1016/j.cie.2007.12.020

Ciardiello, F., & Genovese, A. (2023). A comparison between TOPSIS and SAW methods. *Annals of Operations Research, 325*(2), 967-994. https://doi.org/10.1007/s10479-023-05339-w

Corchado-Garcia, J., Zemmour, D., Hughes, T., Bandi, H., Cristea-Platon, T., Lenehan, P., Pawlowski, C., Bade, S., O'Horo, J. C., Gores, G. J., Williams, A. W., Badley, A. D., Halamka, J., Virk, A., Swift, M. D., Wagner, T., & Soundararajan, V. (2021). Analysis of the effectiveness of the Ad26. COV2. S adenoviral vector vaccine for preventing COVID-19. *JAMA Network Open, 4*(11), e2132540–e2132540. https://doi.org/10.1001/jamanetworkopen.2021.32540

Cromer, D., Steain, M., Reynaldi, A., Schlub, T. E., Wheatley, A. K., Juno, J. A., Kent, S. J., Triccas, J. A., Khoury, D. S., & Davenport, M. P. (2022). Neutralising antibody titres as predictors of protection against SARS-CoV-2 variants and the impact of boosting: a meta-analysis. *The*

Lancet Microbe, 3(1), e52–e61. https://doi.org/10.1016/S2666-5247(21)00267-6

Dadras, O., Mehraeen, E., Karimi, A., Tantuoyir, M. M., Afzalian, A., Nazarian, N., Mojdeganlou, H., Mirzapour, P., Shamsabadi, A., Dashti, M., Ghasemzadeh, A., Vahedi, F., Shobeiri, P., Pashaei, Z., & SeyedAlinaghi, S. A. (2022). Safety and adverse events related to inactivated COVID-19 vaccines and Novavax; a systematic review. *Archives of Academic Emergency Medicine, 10*(1), e54. https://doi.org/10.22037/aaem.v10i1.1585

Dai, T., & Song, J. S. (2021). Transforming COVID-19 vaccines into vaccination: Challenges and opportunities for management scientists. *Health Care Management Science, 24*(3), 455–459. https://doi.org/10.1007/s10729-021-09563-3

Dey, S., Kurbanzade, A. K., Gel, E. S., Mihaljevic, J., & Mehrotra, S. (2024). Optimization modeling for pandemic vaccine supply chain management: A review and future research opportunities. *Naval Research Logistics (NRL), 71*(7), 9761016. https://doi.org/10.1002/nav.22181

Di Valerio, Z., La Faucia, G., Sold, G., Montalti, M., Lenzi, J., Forcellini, M., Barvas, E., Guttmann, S., Poluzzi, E., Raschi, E., Riccardi, R., Fantini, M. P., Salussolia, A., & Gori, D. (2022). ROCCA cohort study: nationwide results on safety of Gam-COVID-Vac vaccine (Sputnik V) in the Republic of San Marino using active surveillance. *EClinicalMedicine, 49*. https://doi.org/10.1016/j.eclinm.2022.101468

Dighriri, I. M., Alhusayni, K. M., Mobarki, A. Y., Aljerary, I. S., Alqurashi, K. A., Aljuaid, F. A., Alamri, K. A., Mutwalli, A. A., Maashi, N. A., Aljohani, A. M., Alqarni, A. M., Alfaqih, A. E., Moazam, S. M., Almutairi, M. N., & Almutairi, A. N. (2022). Pfizer-BioNTech COVID-19 vaccine (BNT162b2) side effects: a systematic review. *Cureus, 14*(3). https://doi.org/10.7759/cureus.23526

Duintjer Tebbens, R. J., & Thompson, K. M. (2018). Using integrated modeling to support the

global eradication of vaccine-preventable diseases. *System Dynamics Review, 34*(12), 78120. https://doi.org/10.1002/sdr.1589

Ella, R., Reddy, S., Blackwelder, W., Potdar, V., Yadav, P., Sarangi, V., Aileni, V. K., Kanungo, S., Rai, S., Reddy, P., Verma, S., Singh, C., Redkar, S., Mohapatra, S., Pandey, A., Ranganadin, P., Gumashta, R., Multani, M., Mohammad, S., Bhatt, P., Kumari, L., Sapkal, G., Gupta, N., Abraham, P., Panda, S., Prasad, S., Bhargava, B., Ella, K., & Vadrevu, K. M. (2021). Efficacy, safety, and lot-to-lot immunogenicity of an inactivated SARS-CoV-2 vaccine (BBV152): interim results of a randomised, double-blind, controlled, phase 3 trial. *The Lancet, 398*(10317), 2173–2184. https://doi.org/10.1016/S0140-6736(21)02000-6

European Medicines Agency. (2021). *AstraZeneca's COVID 19 vaccine: EMA finds possible link to very rare cases of unusual blood clots with low blood platelets* [News item]. Retrieved July 5, 2025, from https://tinyurl.com/emaAstraZenecacideffect

European Medicines Agency. (2021). *COVID 19 Vaccine AstraZeneca: Product information as approved by the Committee for Medicinal Products for Human Use, pending endorsement by the European Commission* [PDF]. Retrieved July 5, 2025, from https://tinyurl.com/EMAAstraZenecaProfile

Fairchild, G., Tasseff, B., Khalsa, H., Generous, N., Daughton, A. R., Velappan, N., & Deshpande, A. (2018). Epidemiological data challenges: planning for a more robust future through data standards. *Frontiers in Public Health, 6*, 336. https://doi.org/10.3389/fpubh.2018.00336

Falsey, A. R., Sobieszczyk, M. E., Hirsch, I., Sproule, S., Robb, M. L., Corey, L., Neuzil, K. M., Hahn, W., Hunt, J., Mulligan, M. J., McEvoy, C., DeJesus, E., Hassman, M., Little, S. J., Pahud, B. A., Durbin, A., Pickrell, P., Daar, E. S., Bush, L., Solis, J., Osuna Carr, Q., Oyedele, T., Buchbinder, S., Cowden, J., Vargas, S. L., Guerreros Benavides, A., Call, R., Keefer, M.

C., Kirkpatrick, B. D., Pullman, J., Tong, T., Brewinski Isaacs, M., Benkeser, D., Janes, H. E., Nason, M. C., Green, J. A., Kelly, E. J., Maaske, J., Mueller, N., Shoemaker, K., Takas, T., Marshall, R. P., Pangalos, M. N., Villafana, T., & Gonzalez-Lopez, A. (2021). Phase 3 safety and efficacy of AZD1222 (ChAdOx1 nCoV-19) Covid-19 vaccine. *New England Journal of Medicine, 385*(25), 2348–2360. https://doi.org/10.1056/NEJMoa2105290

Ferranna, M., Sevilla, J. P., & Bloom, D. E. (2021). *Addressing the COVID-19 pandemic: Comparing alternative value frameworks* (NBER Working Paper No. 28601). National Bureau of Economic Research. https://doi.org/10.2139/ssrn.3803725

Fisher, M. L., Kharenko, K., Ucel, C., & Yadav, P. (2021). Building the supply chain for COVID-19 vaccines. *Cases in Global Health Delivery*. Global Health Delivery Project at Harvard University. Retrieved July 5, 2025, from https://hbsp.harvard.edu/product/GHD045-PDF-ENG

Forestal, R. L., & Pi, S. M. (2022). A hybrid approach based on ELECTRE IIIgenetic algorithm and TOPSIS method for selection of optimal COVID19 vaccines. *Journal of MultiCriteria Decision Analysis, 29*(1–2), 80–91. https://doi.org/10.1002/mcda.1772

Franco, C., Cornejo, A., Rodrguez, M., Garca, A., Belisario, I., Mayora, S., Garzaro, D. J., Jaspe, R. C., Hidalgo, M., Parra, N., Liprandi, F., Zambrano, J. L., Rangel, H. R., & Pujol, F. H. (2024). Sputnik V-induced antibodies against SARS-CoV-2 variants during the dissemination of the Gamma variant in Venezuela. *Viruses, 16*(9), 1480. https://doi.org/10.3390/v16091480

Gajpal, Y., Appadoo, S. S., Shi, V., & Hu, G. (2022). Optimal multi-stage group partition for efficient coronavirus screening. *Annals of Operations Research*, 1-17. https://doi.org/10.1007/s10479-022-04543-4

Gee, J., Marquez, P., Su, J., Calvert, G. M., Liu, R., Myers, T., Nair, N., Martin, S., Clark, T., Markowitz, L., Lindsey, N., Zhang, B., Licata, C., Jazwa, A., Sotir, M., & Shimabukuro,

T. (2021). First month of COVID-19 vaccine safety monitoring–United States, December 14, 2020–January 13, 2021. *Morbidity and Mortality Weekly Report, 70*(8), 283288. https://doi.org/10.15585/mmwr.mm7008e3

Gilbert, P. B., Montefiori, D. C., McDermott, A. B., Fong, Y., Benkeser, D., Deng, W., Zhou, H., Houchens, C. R., Martins, K., Jayashankar, L., Castellino, F., Flach, B., Lin, B. C., O'Connell, S., McDanal, C., Eaton, A., Sarzotti-Kelsoe, M., Lu, Y., Yu, C., Borate, B., van der Laan, L. W. P., Hejazi, N. S., Huynh, C., Miller, J., El Sahly, H. M., Baden, L. R., Baron, M., De La Cruz, L., Gay, C., Kalams, S., Kelley, C. F., Andrasik, M. P., Kublin, J. G., Corey, L., Neuzil, K. M., Carpp, L. N., Pajon, R., Follmann, D., Donis, R. O., & Koup, R. A.; Immune Assays Team; Moderna, Inc. Team; Coronavirus Vaccine Prevention Network (CoVPN)/Coronavirus Efficacy (COVE) Team; & United States Government (USG)/CoVPN Biostatistics Team. (2022). Immune correlates analysis of the mRNA-1273 COVID-19 vaccine efficacy clinical trial. *Science, 375*(6576), 43–50. https://doi.org/10.1126/science.abm3425

Gondwe, G. (2021, May 19). *Malawi destroys 20,000 expired doses of AstraZeneca vaccine*. AP News. https://tinyurl.com/Malawiexpired

Gorbalenya, A. E., Baker, S. C., Baric, R. S., de Groot, R. J., Drosten, C., Gulyaeva, A. A., Haagmans, B. L., Lauber, C., Leontovich, A. M., Neuman, B. W., Penzar, D., Perlman, S., L. L. M., Samborskiy, D. V., Sidorov, I. A., Sola, I., & Ziebuhr, J. (2020). The species severe acute respiratory syndrome-related coronavirus: Classifying 2019-nCoV and naming it SARS-CoV-2. *Nature Microbiology, 5*, 536544. https://doi.org/10.1038/s41564-020-0695-z

Gammudi, K. A. M. (2023). *Safety of COVID-19 Vaccines in Real-World Studies* (Doctoral dissertation, The Claremont Graduate University).

Höpping, A. M., Fonville, J. M., Russell, C. A., James, S., & Smith, D. J. (2016). Influenza

B vaccine lineage selectionan optimized trivalent vaccine. *Vaccine, 34*(13), 16171622. https://doi.org/10.1016/j.vaccine.2016.01.042

Haider, T., Abidi, S. R. Z., Fatima, M., Zafar, A., Siddiqui, R. Q. U., Khan, W., Saeed, T., Anwar, A., & Hashmi, A. A. (2023). The prevalence of side effects of Sinopharm COVID-19 vaccine: An experience from Pakistan. *Cureus, 15*(4). https://doi.org/10.7759/cureus.38180

Hayman, B., Suri, R. K., & Downham, M. (2022). Sustainable vaccine manufacturing in low- and middle-income countries. *Vaccine, 40*(50), 7288–7304. https://doi.org/10.1016/j.vaccine.2022.10.044

Hause, A. M., Marquez, P., Zhang, B., Moro, P. L., Myers, T. R., Bradley, C., Bazel, S., Panchanathan, S., Shimabukuro, T. T., & Shay, D. K. (2022). Safety monitoring of Pfizer-BioNTech COVID-19 vaccine booster doses among children aged 5–11 years–United States, May 17–July 31, 2022. *Morbidity and Mortality Weekly Report, 71*(33), 1092–1097. https://doi.org/10.15585/mmwr.mm7133a3

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative research. *Evidence-Based Nursing, 18*(3), 66–67. https://doi.org/10.1136/eb-2015-102129

Health Canada. (2024). *Moderna Spikevax COVID-19 vaccines*. Retrieved July 5, 2025, from https://www.canada.ca/en/health-canada/services/drugs-health-products/covid19-industry/drugs-vaccines-treatments/vaccines/moderna.html

Health Canada. (2021). *Moderna Spikevax COVID-19 vaccines* [Web page]. Government of Canada. Retrieved July 5, 2025, from https://www.canada.ca/en/health-canada/services/drugs-health-products/covid19-industry/drugs-vaccines-treatments/vaccines/astrazeneca.html

Heath, P. T., Galiza, E. P., Baxter, D. N., Boffito, M., Browne, D., Burns, F., Chadwick, D. R., Clark, R., Cosgrove, C., Galloway, J., Goodman, A. L., Heer, A., Higham, A., Iyengar, S., Jamal, A., Jeanes, C., Kalra, P. A., Kyriakidou, C., McAuley, D. F., Meyrick, A., Minassian, A. M., Minton, J., Moore, P., Munsoor, I., Nicholls, H., Osanlou, O., Packham, J., Pretswell, C. H., San Francisco Ramos, A., Saralaya, D., Sheridan, R. P., Smith, R., Soiza, R. L., Swift, P. A., Thomson, E. C., Turner, J., Viljoen, M. E., Albert, G., Cho, I., Dubovsky, F., Glenn, G., Rivers, J., Robertson, A., Smith, K., & Toback, S. (2021). Safety and efficacy of NVX-CoV2373 Covid-19 vaccine. *New England Journal of Medicine, 385*(13), 1172–1183. https://doi.org/10.1056/NEJMoa2107659

Holleran, A., Martonosi, S. E., & Veatch, M. (2023). International vaccine allocation: An optimization framework [Preprint]. *arXiv*. https://doi.org/10.48550/arXiv.2303.05917

Hou, Y., & Bidkhori, H. (2024). Multi-feature SEIR model for epidemic analysis and vaccine prioritization. *PLOS ONE, 19*(3), e0298932. https://doi.org/10.1371/journal.pone.0298932

Hsu, L. C. (2013). Investment decision making using a combined factor analysis and entropy-based TOPSIS model. *Journal of Business Economics and Management, 14*(3). https://doi.org/10.3846/16111699.2011.633098

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications: A state of the art survey*. Springer-Verlag. http://dx.doi.org/10.1007/978-3-642-48318-9

Hwang, C. L., & Yoon, K. P. (1995). *Multiple attribute decision making: An introduction*. SAGE Publications Inc. https://doi.org/10.4135/9781412985161

Ikegame, S., Siddiquey, M. N. A., Hung, C.-T., Haas, G., Brambilla, L., Oguntuyo, K. Y., Kowdle, S., Chiu, H.-P., Stevens, C. S., Vilardo, A. E., Edelstein, A., Perandones, C., Kamil, J.

P., & Lee, B. (2021). Neutralizing activity of Sputnik V vaccine sera against SARS-CoV-2 variants. *Nature Communications, 12*(1), 4598. https://doi.org/10.1038/s41467-021-24909-9

Irurzun-Lopez, M., Oyatoye, I., & Griffiths, U. K. (2023). *Covid-19 vaccine prices and procurement in low- and middle-income countries during the height of the Covid-19 pandemic*. Immunization Economics. Retrieved July 5, 2025, from https://immunizationeconomics.org/wp-content/uploads/2024/01/Maite-Lopez-COVID-vaccine-priceprocurement-analaysis_11July2023.pdf

Islam, M. S., Kamal, A.-H. M., Kabir, A., Southern, D. L., Khan, S. H., Hasan, S. M. M., Sarkar, T., Sharmin, S., Das, S., Roy, T., Harun, M. G. D., Chughtai, A. A., Homaira, N., & Seale, H. (2021). COVID-19 vaccine rumors and conspiracy theories: The need for cognitive inoculation against misinformation to improve vaccine adherence. *PloS One, 16*(5), e0251605. https://doi.org/10.1371/journal.pone.0251605

Jangra, K. K., Sharma, N., Khanna, R., & Matta, D. (2016). An experimental investigation and optimization of friction stir welding process for AA6082 T6 (cryogenic treated and untreated) using an integrated approach of Taguchi, grey relational analysis and entropy method. *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 230*(2), 454-469. https://doi.org/10.1177/1464420715578182

Jara, A., Undurraga, E. A., Gonzlez, C., Paredes, F., Fontecilla, T., Jara, G., Pizarro, A., Acevedo, J., Leo, K., Leon, F., Sans, C., Leighton, P., Suarez, P., Garca-Escorza, H., & Araos, R. (2021). Effectiveness of an inactivated SARS-CoV-2 vaccine in Chile. *New England Journal of Medicine, 385*(10), 875–884. https://doi.org/10.1056/NEJMoa2107715

Johnson & Johnson Inc. (2021). *Johnson & Johnson single shot COVID-19 vaccine phase 3 data*

published in New England Journal of Medicine [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/jnjefficacy

Johnson & Johnson Inc. (2022). *World Health Organization updated Emergency Use Listing recommends Johnson & Johnson COVID19 vaccine for booster use* [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/jnjemeregencyuse

Jones, I., & Roy, P. (2021). Sputnik V COVID-19 vaccine candidate appears safe and effective. *The Lancet, 397*(10275), 642–643. https://doi.org/10.1016/S0140-6736(21)00191-4

Joshi, K., Rumpler, E., Kennedy-Shaffer, L., Bosan, R., & Lipsitch, M. (2021). Comparative performance of between-population allocation strategies for SARS-CoV-2 vaccines [Preprint]. *medRxiv*. https://doi.org/10.1101/2021.06.18.21259137

Kandulu, C. C., Sahm, L. J., Saab, M. M., O'Driscoll, M., McCarthy, M., Shorter, G. W., Berry, E., Moore, A. C., & Fleming, A. (2024). A scoping review of factors affecting COVID-19 vaccination uptake and deployment in global healthcare systems. *Vaccines, 12*(10), 1093. https://doi.org/10.3390/vaccines12101093

Karim, S. S. A., & Karim, Q. A. (2021). Omicron SARS-CoV-2 variant: a new chapter in the COVID-19 pandemic. *The Lancet, 398*(10317), 2126–2128. https://doi.org/10.1016/S0140-6736(21)02758-6

Kaur, U., Anju, K. L., Chauhan, M., Joshi, A., Das, A., Kansal, S., Jaisawal, V., Patwardhan, K., & Chakrabarti, S. S. (2022). A prospective observational study on BBV152 coronavirus vaccine use in adolescents and comparison with adults: Interim results of the first real-world safety analysis. *Drug Safety, 45*(10), 1099–1109. https://doi.org/10.1007/s40264-022-01226-8

Kidangoor, A. (2022, January 19). *The world's largest vaccine manufacturer stumbled in 2021. Its*

CEO bets he can still help end COVID-19. Time. Retrieved June 20, 2025, from https://time.com/6132402/serum-institue-of-india-covid-19-vaccine/

King, M. L. (2024). How manufacturing won or lost the COVID-19 vaccine race. *Vaccine, 42*(5), 1004–1012. https://doi.org/10.1016/j.vaccine.2023.12.031

Kizielewicz, B., Tomczyk, T., Gandor, M., & Saabun, W. (2024). Subjective weight determination methods in multi-criteria decision-making: A systematic review. *Procedia Computer Science, 246*, 5396–5407. https://doi.org/10.1016/j.procs.2024.09.673

Kollewe, J. (2021, August 11). *Covid-19 vaccines: The contracts, prices and profits*. *The Guardian*. Retrieved July 5, 2025, from https://www.theguardian.com/world/2021/aug/11/covid-19-vaccines-the-contracts-prices-and-profits

Leek, J. T., & Peng, R. D. (2015). Reproducible research can still be wrong: Adopting a prevention approach. *Proceedings of the National Academy of Sciences of the United States of America, 112*(6), 1645–1646. https://doi.org/10.1073/pnas.1421412111

Li, J., Li, X., Wang, E., Yang, J., Li, J., Huang, C., Zhang, Y., & Chen, K. (2022). Neutralizing antibodies against the SARS-CoV-2 delta and omicron BA.1 following homologous CoronaVac booster vaccination. *Vaccines, 10*(12), 2111. https://doi.org/10.3390/vaccines10122111

Li, X., Wang, K., Liu, L., Xin, J., Yang, H., & Gao, C. (2011). Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. *Procedia Engineering, 26*, 2085–2091. https://doi.org/10.1016/j.proeng.2011.11.2410

Light, D. W., & Lexchin, J. (2021). The costs of coronavirus vaccines and their pricing. *Journal of the Royal Society of Medicine, 114*(11), 502–504. https://doi.org/10.1177/01410768211053006

Logunov, D. Y., Dolzhikova, I. V., Shcheblyakov, D. V., Tukhvatulin, A. I., Zubkova, O. V., Dzharullaeva, A. S., Kovyrshina, A. V., Lubenets, N. L., Grousova, D. M., Erokhova, A. S., Botikov, A. G., Izhaeva, F. M., Popova, O., Ozharovskaya, T. A., Esmagambetov, I. B., Favorskaya, I. A., Zrelkin, D. I., Voronina, D. V., Shcherbinin, D. N., Semikhin, A. S., Simakova, Y. V., Tokarskaya, E. A., Egorova, D. A., Shmarov, M. M., Nikitenko, N. A., Gushchin, V. A., Smolyarchuk, E. A., Zyryanov, S. K., Borisevich, S. V., Naroditsky, B. S., & Gintsburg, A. L. (2021). Safety and efficacy of an rAd26 and rAd5 vector-based heterologous prime-boost COVID-19 vaccine: an interim analysis of a randomised controlled phase 3 trial in Russia. *The Lancet, 397*(10275), 671–681. https://doi.org/10.1016/S0140-6736(21)00234-8

Luczkowiak, J., Rivas, G., Labiod, N., Lasala, F., Rolo, M., Lora-Tamayo, J., Mancheno-Losa, M., Rial-Crestelo, D., Prez-Rivilla, A., Folgueira, M. D., & Delgado, R. (2023). Cross neutralization of SARS-CoV-2 omicron subvariants after repeated doses of COVID-19 mRNA vaccines. *Journal of Medical Virology, 95*(1), e28268. https://doi.org/10.1002/jmv.28268

Madhi, S. A., Kwatra, G., Richardson, S. I., Koen, A. L., Baillie, V., Cutland, C. L., Fairlie, L., Padayachee, S. D., Dheda, K., Barnabas, S. L., Bhorat, Q. E., Briner, C., Ahmed, K., Aley, P. K., Bhikha, S., Bhorat, A. E., Esmail, A., Horne, E., Kaldine, H., Mukendi, C. K., Madzorera, V. S., Manamela, N. P., Masilela, M., Hermanus, S. T., Motlou, T., Mzindle, N., Oelofse, S., Patel, F., Rhead, S., Rossouw, L., Taoushanis, C., van Eck, S., Lambe, T., Gilbert, S. C., Pollard, A. J., Moore, P. L., & Izu, A. (2023). Durability of ChAdOx1 nCoV-19 (AZD1222) vaccine and hybrid humoral immunity against variants including omicron BA.1 and BA.4 6 months after vaccination (COV005): a post-hoc analysis of a randomised, phase 1b–2a trial. *The Lancet Infectious Diseases, 23*(3), 295–306. https://doi.org/10.1016/S1473-3099(22)00596-5

Mak, H. Y., Dai, T., & Tang, C. S. (2022). Managing two dose COVID19 vaccine rollouts with

limited supply: Operations strategies for distributing timesensitive resources. *Production and Operations Management, 31*(12), 4424–4442. https://doi.org/10.1111/poms.13862

Mallick, R., Pramanik, S., & Giri, B. C. (2024). TOPSIS and VIKOR strategies for COVID-19 vaccine selection in QNN environment. *OPSEARCH, 61*(4), 2072-2094. https://doi.org/10.1007/s12597-024-00766-0

Manheim, D., Chamberlin, M., Osoba, O. A., Vardavas, R., & Moore, M. (2016). *Improving decision support for infectious disease prevention and control: Aligning models and other tools with policymakers' needs* (RR-1576-OSD). RAND Corporation. Retrieved from https://www.rand.org/pubs/research_reports/RR1576.html

Masood, A., Chohan, H. K., Mubeen, M., Faizan, M., Moin, S., Chohan, M. K., Syed, T., Anwar, A., & Hashmi, A. A. (2023). Sinovac COVID-19 side effects in hypertensive patients: An observational study from Pakistan. *Cureus, 15*(6). https://doi.org/10.7759/cureus.40444

Mathieu, E., Ritchie, H., Rods-Guirao, L., Appel, C., Gavrilov, D., Giattino, C., Hasell, J., Macdonald, B., Dattani, S., Beltekian, D., Ortiz-Ospina, E., & Roser, M. (n.d.). *Coronavirus (COVID-19) vaccinations*. Our World in Data. Retrieved June 11, 2025, from https://ourworldindata.org/covid-vaccinations

Mathieu, E., Ritchie, H., Rods-Guirao, L., Appel, C., Gavrilov, D., Giattino, C., Hasell, J., Macdonald, B., Dattani, S., Beltekian, D., Ortiz-Ospina, E., & Roser, M. (n.d.). *Coronavirus (COVID-19) deaths*. Our World in Data. Retrieved June 10, 2025, from https://ourworldindata.org/covid-deaths

Medicines & Healthcare products Regulatory Agency. (2023). *Information for healthcare professionals on COVID-19 vaccine AstraZeneca (Regulation 174)* [Web page]. GOV.UK. Retrieved July 5, 2025, from https://tinyurl.com/MHRAAstraZenecaProfile

Meeraus, W., de Munter, L., Gray, C. M., Dwivedi, A., Wyndham-Thomas, C., Ouwens, M., Hartig-Merkel, W., Drikite, L., Rebry, G., Carmona, A., Stuurman, A. L., Nguyen, T. Y. C., Mena, G., Mira-Iglesias, A., Icardi, G., Otero-Romero, S., Baumgartner, S., Martin, C., Taylor, S., & Bollaerts, K. (2023). Protection against COVID-19 hospitalisation conferred by primary-series vaccination with AZD1222 in non-boosted individuals: first vaccine effectiveness results of the European COVIDRIVE study and meta-regression analysis. *The Lancet Regional Health–Europe, 31*. https://doi.org/10.1016/j.lanepe.2023.100675

Ministry of Health (Ontario). (2024). *Chapter 1: Storage and handling of Pfizer-BioNTech's COVID-19 vaccines* (Version 8.0) [PDF]. Government of Ontario. Retrieved July 5, 2025, from https://www.ontario.ca/files/2024-10/moh-chapter-1-pfizer-vsh-en-2024-10-24.pdf

Montalti, M., Sold, G., Di Valerio, Z., Salussolia, A., Lenzi, J., Forcellini, M., Barvas, E., Guttmann, S., Messina, R., Poluzzi, E., Raschi, E., Riccardi, R., Fantini, M. P., La Fauci, G., & Gori, D. (2021). ROCCA observational study: Early results on safety of Sputnik V vaccine (Gam-COVID-Vac) in the Republic of San Marino using active surveillance. *EClinicalMedicine, 38*. https://doi.org/10.1016/j.eclinm.2021.101027

Moradi, M., Zareiyan, A., Sharififar, S., Nasiri, A., & Hosseini Shokouh, S. J. (2023). Designing the structural model of temporary medical centers in biological emergencies. *International Journal of Healthcare Management, 18*(1), 28-37. https://doi.org/10.1080/20479700.2023.2264033

National Institutes of Health, Islamabad. (2021, October 20). *Guidelines for Sputnik V vaccine: Storage, handling, administration, and safe disposal* [PDF]. National Institutes of Health, Islamabad. Retrieved July 5, 2025, from https://www.nih.org.pk/wp-content/uploads/2021/10/20211020-Guidelines-for-Sputnik-V-Vaccine_6103.pdf

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research, 156*(2), 445455. https://doi.org/10.1016/S0377-2217(03)00020-1

Pan American Health Organization & World Health Organization. (n.d.). *Sinovac COVID-19 vaccine (CoronaVac)* [Web page]. Retrieved July 5, 2025, from https://covid-19pharmacovigilance.paho.org/sinovac

Pan American Health Organization. (2022). *COVID-19 pandemic response. In Health in the Americas*. Retrieved August 12, 2025, from https://hia.paho.org/en/covid-2022/response

Patil, D. R., Shete, A. M., Yadav, P. D., Sapkal, G. N., Deshpande, G. R., Kaushal, H., Mohandas, S., Fulari, S., Jain, R., Kumar, A., & Abraham, P. (2023). Host immune responses in aged rhesus macaques against BBV152, an inactivated SARS-CoV-2 vaccine, and cross-neutralization with beta and delta variants. *Frontiers in Immunology, 14*, 1161571. https://doi.org/10.3389/fimmu.2023.1161571

Peng, R. D. (2011). Reproducible research in computational science. *Science, 334*(6060), 1226–1227. https://doi.org/10.1126/science.1213847

Pfizer Inc. (2022, December 8). *Pfizer BioNTech COVID 19 VaccineStorage and Handling; Dosage and Administration; Use in Specific Populations* [Fact sheet]. Pfizer Inc. Retrieved July 5, 2025, from https://labeling.pfizer.com/ShowLabeling.aspx?id=16072

Polack, F. P., Thomas, S. J., Kitchin, N., Absalon, J., Gurtman, A., Lockhart, S., Perez, J. L., Prez Marc, G., Moreira, E. D., Zerbini, C., Bailey, R., Swanson, K. A., Roychoudhury, S., Koury, K., Li, P., Kalina, W. V., Cooper, D., Frenck, R. W., Hammitt, L. L., Treci, ., Nell, H., Schaefer, A., Unal, S., Tresnan, D. B., Mather, S., Dormitzer, P. R., Sahin, U., Jansen, K. U., & Gruber, W. C. (2020). Safety and efficacy of the BNT162b2

mRNA Covid-19 vaccine. *New England Journal of Medicine, 383*(27), 2603–2615. https://doi.org/10.1056/NEJMoa2034577

Ponhan, K., & Sureeyatanapas, P. (2022). A comparison between subjective and objective weighting approaches for multi-criteria decision making: A case of industrial location selection. *Engineering and Applied Science Research, 49*(6), 763–771. https://doi.org/10.14456/easr.2022.74

Public Health Agency of Canada. (2025, February 5). *COVID-19 vaccine (Canadian Immunization Guide, Part 4)*. Government of Canada. Retrieved July 5, 2025, from https://www.canada.ca/en/public-health/services/publications/healthy-living/canadian-immunization-guide-part-4-active-vaccines/page-26-covid-19-vaccine.html

Puranam, E. (2021, May 24). *India crosses 300,000 COVID-19 deaths; vaccine drive hit by shortage*. Al Jazeera. Retrieved June 20, 2025, from https://www.aljazeera.com/news/2021/5/24/india-crosses-300000-covid-deaths-vaccine-drive-hit-by-shortage

Ramatillah, D. L., Gan, S. H., Novarticia, J., Araminda, G. N., Michael, M., Elnaem, M., Alawuddin, R., & Khan, K. (2024). Side effects of CoronaVac® COVID-19 vaccination: Investigation in North Jakarta district public health center communities in Indonesia. *Heliyon, 10*(9). https://doi.org/10.1016/j.heliyon.2024.e30087

Riad, A., Sagroglu, D., Ustun, B., Pokorna, A., Klugarova, J., Attia, S., & Klugar, M. (2021). Prevalence and risk factors of CoronaVac side effects: An independent cross-sectional study among healthcare workers in Turkey. *Journal of Clinical Medicine, 10*(12), 2629. https://doi.org/10.3390/jcm10122629

Roy, B. (1991). The outranking approach and the foundations of ELECTRE methods. *Theory and Decision, 31*, 4973. http://dx.doi.org/10.1007/978-3-642-75935-2_8

Roy, D. N., Biswas, M., Islam, E., & Azam, M. S. (2022). Potential factors influencing COVID-19 vaccine acceptance and hesitancy: A systematic review. *PloS One, 17*(3), e0265496. https://doi.org/10.1371/journal.pone.0265496

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences, 1*(1), 8398. https://doi.org/10.1504/IJSSCI.2008.017590

Saaty, T. L., & Tran, L. T. (2007). On the invalidity of fuzzifying numerical judgments in the Analytic Hierarchy Process. *Mathematical and Computer Modelling, 46*(78), 962975. https://doi.org/10.1016/j.mcm.2007.03.022

Sadoff, J., Gray, G., Vandebosch, A., Crdenas, V., Shukarev, G., Grinsztejn, B., Goepfert, P. A., Truyers, C., Fennema, H., Spiessens, B., Offergeld, K., Scheper, G., Taylor, K. L., Robb, M. L., Treanor, J., Barouch, D. H., Stoddard, J., Ryser, M. F., Marovich, M. A., Neuzil, K. M., Corey, L., Cauwenberghs, N., Tanner, T., Hardt, K., Ruiz-Guiaz, J., Le Gars, M., Schuitemaker, H., Van Hoof, J., Struyf, F., & Douoguih, M. (2021). Safety and efficacy of single-dose Ad26.COV2.S vaccine against Covid-19. *New England Journal of Medicine, 384*(23), 2187–2201. https://doi.org/10.1056/NEJMoa2101544

Selbe, J., & Podlutsky, A. (2024). Adverse side effects of COVID-19 vaccines in older adults: A comprehensive review of current research. *Advances in Aging Research, 13*(6), 121–135. https://doi.org/10.4236/aar.2024.136009

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*(3), 379-423. http://dx.doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sharma, M., & Pandey, A. (2021, April 25). *Covaxin will cost Rs 600 per dose for state governments, Rs 1,200 for private hospitals: Bharat Biotech*. India Today. Retrieved July 5, 2025, from https://tinyurl.com/IndiaTodayCovaxinPrice

Shay, D. K. (2021). Safety monitoring of the Janssen (Johnson & Johnson) COVID-19 vaccine–United States, March–April 2021. *MMWR. Morbidity and Mortality Weekly Report, 70*. https://doi.org/10.15585/mmwr.mm7018e2

Sheen, G. C. H., Tung, H. H., Wu, C. H., & Wu, W. C. (2023). WHO approves? Relative trust, the WHO, and China's COVID-19 vaccines. *The Review of International Organizations, 18*(3), 499–521. Retrieved from https://doi.org/10.1007/s11558-022-09481-1

Shinde, V., Bhikha, S., Hoosain, Z., Archary, M., Bhorat, Q., Fairlie, L., Lalloo, U., Masilela, M. S. L., Moodley, D., Hanley, S., Fouche, L., Louw, C., Tameris, M., Singh, N., Goga, A., Dheda, K., Grobbelaar, C., Kruger, G., Carrim-Ganey, N., Baillie, V., de Oliveira, T., Koen, A. L., Lombaard, J. J., Mngqibisa, R., Bhorat, A. E., Benad, G., Lalloo, N., Pitsi, A., Vollgraaff, P. L., Luabeya, A., Esmail, A., Petrick, F. G., Oommen-Jose, A., Foulkes, S., Ahmed, K., Thombrayil, A., Fries, L., Cloney-Clark, S., Zhu, M., Bennett, C., Albert, G., Faust, E., Plested, J. S., Robertson, A., Neal, S., Cho, I., Glenn, G. M., Dubovsky, F., & Madhi, S. A. (2021). Efficacy of NVX-CoV2373 Covid-19 vaccine against the B.1.351 variant. *New England Journal of Medicine, 384*(20), 1899–1909. https://doi.org/10.1056/NEJMoa2103055

Singh, M., & Pant, M. (2021). A review of selected weighing methods in MCDM with a case study. *International Journal of System Assurance Engineering and Management, 12*(1), 126-144. https://doi.org/10.1007/s13198-020-01033-3

Sinuraya, R. K., Nuwarda, R. F., Postma, M. J., & Suwantika, A. A. (2024). Vaccine hesitancy and equity: Lessons learned from the past and how they affect the COVID-19 countermeasure in Indonesia. *Globalization and Health, 20*(1), 11. https://doi.org/10.1186/

s12992-023-00987-w

Soheili, M., Khateri, S., Moradpour, F., Mohammadzedeh, P., Zareie, M., Mahdavi Mortazavi, S. M., Manifar, S., Gilzad Kohan, H., & Moradi, Y. (2023). The efficacy and effectiveness of COVID-19 vaccines around the world: A mini-review and meta-analysis. *Annals of Clinical Microbiology and Antimicrobials, 22*(1), 42. https://doi.org/10.1186/s12941-023-00594-y

Sotoudeh-Anvari, A. (2022). The applications of MCDM methods in COVID-19 pandemic: A state of the art review. *Applied Soft Computing, 126*, 109238. https://doi.org/10.1016/j.asoc.2022.109238

Su, J., & Sun, Y. (2023). An improved TOPSIS model based on cumulative prospect theory: Application to ESG performance evaluation of state-owned mining enterprises. *Sustainability, 15*(13), 10046. https://doi.org/10.3390/su151310046

Sukhikh, G. T., Priputnevich, T. V., Ogarkova, D. A., Pochtovyi, A. A., Kustova, D. D., Zlobin, V. I., Logunov, D. Y., Gushchin, V. A., & Gintsburg, A. L. (2022). Sputnik Light and Sputnik V vaccination is effective at protecting medical personnel from COVID-19 during the period of Delta variant dominance. *Vaccines, 10*(11), 1804. https://doi.org/10.3390/vaccines10111804

Tan-Torres Edejer, T., Baltussen, R. M., Adam, T., Hutubessy, R. C., Acharya, A., Evans, D. B., & World Health Organization. (2003). *Making choices in health: WHO guide to cost-effectiveness analysis*. World Health Organization. https://iris.who.int/handle/10665/42699

Tanriover, M. D., Doganay, H. L., Akova, M., Guner, H. R., Azap, A., Akhan, S., Kose, S., Erdinc, F. S., Akaln, E. H., Tabak, O. F., Pullukcu, H., Batum, O., Simsek Yavuz, S., Turhan, O., Yldrmak, M. T., Koksal, ., Taova, Y., Korten, V., Ylmaz, G., Celen, M. K., Altn, S., Celik, I., Bayndr, Y., Karaoglan, I., Ylmaz, A., Ozkul, A., Gur, H., & Unal, S. (2021). Efficacy and

safety of an inactivated whole-virion SARS-CoV-2 vaccine (CoronaVac): interim results of a double-blind, randomised, placebo-controlled, phase 3 trial in Turkey. *The Lancet, 398*(10296), 213–222. https://doi.org/10.1016/S0140-6736(21)01429-X

The Gamaleya Research Centre. (2021, April 26). *The Gamaleya Center statement on increasing the interval between first and second Sputnik V vaccine shots* [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/GamaleyaSputnicV

The Gamaleya Research Centre. (2020, November 24). *Second interim analysis of clinical trial data showed a 91.4% efficacy for the Sputnik V vaccine on day 28 after the first dose* [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/GamaleyaSputnicVEfficacy

The Gamaleya Research Centre. (2021). *About Sputnik V* [Web page]. Retrieved July 5, 2025, from https://sputnikvaccine.com/about-vaccine/

The Gamaleya Research Centre. (2020, November 24). *The cost of one dose of the Sputnik V vaccine will be less than $10 for international markets* [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/Sputnikdose

Tregoning, J. S., Flight, K. E., Higham, S. L., Wang, Z., & Pierce, B. F. (2021). Progress of the COVID-19 vaccine effort: Viruses, vaccines and variants versus efficacy, effectiveness and escape. *Nature Reviews Immunology, 21*(10), 626–636. https://doi.org/10.1038/s41577-021-00592-1

Triantaphyllou, E. (2000). *Multi-criteria decision making methods: A comparative study*. Kluwer Academic Publishers.

Tseng, H. F., Ackerson, B. K., Luo, Y., Sy, L. S., Talarico, C. A., Tian, Y., Bruxvoort, K. J., Tubert, J. E., Florea, A., Ku, J. H., Lee, G. S., Choi, S. K., Takhar, H. S., Aragones, M., & Qian, L. (2022). Effectiveness of mRNA-1273 against SARS-CoV-2 Omicron and

Delta variants. *Nature Medicine, 28*(5), 1063–1071. https://doi.org/10.1038/s41591-022-01753-y

Üner, S. ., Demir, A., Dinler, S., & Alaka, H. M. (2023). Prioritizing individuals who will have COVID-19 vaccine with multi-criteria decision making methods. *Gazi University Journal of Science, 36*(3), 1277–1290. https://doi.org/10.35378/gujs.1053782

U.S. Food and Drug Administration. (2022). *Pfizer-BioNTech COVID-19 vaccine*. Retrieved July 5, 2025, from https://tinyurl.com/FDApfizerBion

U.S. Food and Drug Administration. (2024). *Moderna COVID-19 vaccine* [Web page]. Retrieved July 5, 2025, from https://tinyurl.com/FADModerna

U.S. Food and Drug Administration, & Centers for Disease Control and Prevention. (2021, April 23). *FDA and CDC lift recommended pause on Johnson & Johnson (Janssen) COVID-19 vaccine use following thorough safety review* [Press release]. Retrieved July 5, 2025, from https://tinyurl.com/fdajnjsideffect

U.S. Food and Drug Administration. (2024). *Nuvaxovid COVID-19 vaccine (NVX-CoV2373) package insert* [PDF]. Retrieved July 6, 2025, from https://www.fda.gov/files/vaccines%2C%20blood%20%26%20biologics/published/Package-Insert-and-Patient-Package-Insert-NUVAXOVID.pdf

United Nations Children's Fund. (2023). *COVAX: Ensuring global equitable access to COVID-19 vaccines*. UNICEF Supply Division. Retrieved August 12, 2025, from https://www.unicef.org/supply/covax-ensuring-global-equitable-access-covid-19-vaccines

Utami, A. M., Rendrayani, F., Khoiry, Q. A., Alfiani, F., Kusuma, A. S., & Suwantika, A. A. (2022). Cost-effectiveness analysis of COVID-19 vaccination in low- and middle-income countries. *Journal of Multidisciplinary Healthcare*, 2067–2076. https://doi.org/10.2147/JMDH.S372000

Velasquez, M., & Hester, P. T. (2013). An analysis of multi-criteria decision making methods. *International Journal of Operations Research, 10*(2), 56–66.

Voysey, M., Costa Clemens, S. A., Madhi, S. A., Weckx, L. Y., Folegatti, P. M., Aley, P. K., Angus, B., Baillie, V. L., Barnabas, S. L., Bhorat, Q. E., Bibi, S., Briner, C., Cicconi, P., Collins, A. M., Colin-Jones, R., Cutland, C. L., Darton, T. C., Dheda, K., Duncan, C. J. A., Emary, K. R. W., Ewer, K. J., Fairlie, L., Faust, S. N., Feng, S., Ferreira, D. M., Finn, A., Goodman, A. L., Green, C. M., Green, C. A., Heath, P. T., Hill, C., Hill, H., Hirsch, I., Hodgson, S. H. C., Izu, A., Jackson, S., Jenkin, D., Joe, C. C. D., Kerridge, S., Koen, A., Kwatra, G., Lazarus, R., Lawrie, A. M., Lelliott, A., Libri, V., Lillie, P. J., Mallory, R., Mendes, A. V. A., Milan, E. P., Minassian, A. M., McGregor, A., Morrison, H., Mujadidi, Y. F., Nana, A., O'Reilly, P. J., Padayachee, S. D., Pittella, A., Plested, E., Pollock, K. M., Ramasamy, M. N., Rhead, S., Schwarzbold, A. V., Singh, N., Smith, A., Song, R., Snape, M. D., Sprinz, E., Sutherland, R. K., Tarrant, R., Thomson, E. C., Torok, M. E., Toshner, M., Turner, D. P. J., Vekemans, J., Villafana, T. L., Watson, M. E. E., Williams, C. J., Douglas, A. D., Hill, A. V. S., Lambe, T., Gilbert, S. C., & Pollard, A. J. (2021). Safety and efficacy of the ChAdOx1 nCoV-19 vaccine (AZD1222) against SARS-CoV-2: an interim analysis of four randomised controlled trials in Brazil, South Africa, and the UK. *The Lancet, 397*(10269), 99–111. https://doi.org/10.1016/S0140-6736(20)32661-1

Wen, K. L., Chang, T. C., & You, M. L. (1998). The grey entropy and its application in weighting analysis. In *IEEE International Conference on Systems, Man, and Cybernetics* (Vol. 2, pp. 1842–1844). https://doi.org/10.1109/ICSMC.1998.728163

Williams, B. A., Jones, C. H., Welch, V., & True, J. M. (2023). Outlook of pandemic preparedness in a post-COVID-19 world. *npj Vaccines, 8*(1), 178. https://doi.org/10.1038/s41541-023-00773-0

Wipperman, A. (2022, May 3). *How data can reduce waste and get vaccines where they need to be*. VaccinesWork. Gavi, the Vaccine Alliance. Re-

trieved June 11, 2025, from https://www.gavi.org/vaccineswork/how-data-can-reduce-waste-and-get-vaccines-where-they-need-be

World Health Organization. (2022, May 17). *A healthy return: Investment case for a sustainably financed WHO* [Report]. World Health Organization. Retrieved July 5, 2025, from https://iris.who.int/handle/10665/354372

World Health Organization. (2024, October 8). *Coronavirus disease (COVID-19): Vaccines and vaccine safety* [Questions & Answers]. Retrieved July 5, 2025, from https://www.who.int/news-room/questions-and-answers/item/coronavirus-disease-(covid-19)-vaccines

World Health Organization. (2020, January 9). *Emergency use listing procedure* [Web page]. Retrieved July 5, 2025, from https://extranet.who.int/prequal/vaccines/emergency-use-listing-procedure

World Health Organization. (2021, July 1). *Joint COVAX statement on the equal recognition of vaccines* [Statement]. Retrieved August 10, 2025, from https://tinyurl.com/WHOCOVAX

World Health Organization. (2020, December 31). *WHO issues its first emergency use validation for a COVID-19 vaccine and emphasizes need for equitable global access* [News release]. Retrieved July 5, 2025, from https://tinyurl.com/whoemergencyuse

World Health Organization. (2021, April 30). *WHO lists Moderna vaccine for emergency use* [News release]. Retrieved July 5, 2025, from https://www.who.int/news/item/30-04-2021-who-lists-moderna-vaccine-for-emergency-use

World Health Organization. (2021, March 12). *WHO adds Janssen vaccine to list of safe and effective emergency tools against COVID 19* [News release]. Retrieved July 5, 2025, from https://tinyurl.com/whojnjemeregency

World Health Organization. (2021, April 19). *The Oxford–AstraZeneca COVID-19 vaccine: What you need to know* [Feature story].. Retrieved July 5, 2025, from https://www.who.int/news-room/feature-stories/detail/the-oxford-astrazeneca-covid-19-vaccine-what-you-need-to-know

World Health Organization. (2021, February 15). *WHO lists two additional COVID-19 vaccines for emergency use and COVAX roll-out* [News release]. Retrieved July 5, 2025, from https://tinyurl.com/WHOEmeregencyCovax

World Health Organization. (2023, August 8). *Status of COVID-19 vaccines within WHO EUL/PQ evaluation process* [PDF]. Retrieved July 5, 2025, from https://extranet.who.int/pqweb/key-resources/documents/status-covid-19-vaccines-within-who-eulpq-evaluation-process

World Health Organization. (2022, June 10). *The Sinopharm COVID-19 vaccine: What you need to know* [Feature story]. Retrieved July 5, 2025, from https://www.who.int/news-room/feature-stories/detail/the-sinopharm-covid-19-vaccine-what-you-need-to-know

World Health Organization. (2022, June 3). *COVID-19 Vaccine (Vero Cell), Inactivated (Sinopharm) explainer: Status update 16 June 2022* [PDF]. Retrieved July 5, 2025, from https://cdn.who.int/media/docs/default-source/immunization/covid-19/16-june-22080-sinopharm-vaccine-explainer-update.pdf

World Health Organization. (2022, June 10). *The Sinovac CoronaVac COVID-19 vaccine: What you need to know* [Feature story]. Retrieved July 5, 2025, from https://www.who.int/news-room/feature-stories/detail/the-sinovac-covid-19-vaccine-what-you-need-to-know

World Health Organization. (2021, June 11). *COVID-19 Vaccine (Vero Cell), Inactivated (CoronaVac) explainer: Status update 16 June 2021* [PDF]. Retrieved July 5, 2025,

from https://www.who.int/docs/default-source/coronaviruse/act-accelerator/covax/21221_sinovac-vaccine-explainer.pdf

World Health Organization. (2021, June 1). *WHO validates Sinovac CoronaVac COVID-19 vaccine for emergency use and issues interim policy recommendations* [News release]. Retrieved July 5, 2025, from https://tinyurl.com/WHOEmeregencySinovac

World Health Organization. (2022, June 10). *The Bharat Biotech BBV152 COVAXIN vaccine against COVID-19: What you need to know* [Feature story]. Retrieved July 5, 2025, from https://tinyurl.com/WHOCovaxin

World Health Organization. (2022, January 5). *COVID-19 Vaccine (Whole Virion Inactivated Corona Virus vaccine), BBV152, COVAXIN: Explainer 5 January 2022* [PDF]. Retrieved July 5, 2025, from https://www.who.int/docs/default-source/coronaviruse/7-jan_22006_covaxin_vaccine-explainer_for-web.pdf

World Health Organization. (2021, November 9). *WHO issues emergency use listing for eighth COVID-19 vaccine* [News release]. Retrieved July 5, 2025, from https://tinyurl.com/WHOEmeregencyCovaxin

World Health Organization. (2022, February 4). *COVID-19 Vaccine (Recombinant Nanoparticle Protein, Adjuvanted) NVX CoV2373 (Novavax): Explainer 4 February 2022* [PDF]. Retrieved July 6, 2025, from https://www.who.int/docs/default-source/coronaviruse/4-feb_22015_novavax_vaccine-explainer_for_web.pdf

World Health Organization. (2021, December 17). *WHO lists 9th COVID-19 vaccine for emergency use with aim to increase access to vaccination in lower-income countries* [News release]. Retrieved July 6, 2025, from https://tinyurl.com/WHOEmeregencyNovavax

World Health Organization, Strategic Advisory Group of Experts on Immunization (SAGE). (2021, April 29). *Evidence assessment: Sinopharm/BBIBP COVID-19 vaccine* [PDF]. Retrieved July 5, 2025, from https://cdn.who.int/media/docs/default-source/immunization/sage/2021/april/2_sage29apr2021_critical-evidence_sinopharm.pdf

Wouters, O. J., Shadlen, K. C., Salcher-Konrad, M., Pollard, A. J., Larson, H. J., Teerawattananon, Y., & Jit, M. (2021). Challenges in ensuring global access to COVID-19 vaccines: production, affordability, allocation, and deployment. *The Lancet, 397*(10278), 1023–1034. https://doi.org/10.1016/S0140-6736(21)00306-8

Wu, J., Sun, J., Liang, L., & Zha, Y. (2011). Determination of weights for ultimate cross efficiency using Shannon entropy. *Expert Systems with Applications, 38*(5), 5162–5165. https://doi.org/10.1016/j.eswa.2010.10.046

Wu, R. M. X., Zhang, Z., Yan, W., Fan, J., Gou, J., Liu, B., Gide, E., Soar, J., Shen, B., Fazal-e-Hasan, S., Liu, Z., Zhang, P., Wang, P., Cui, X., Peng, Z., & Wang, Y. (2022). A comparative analysis of the principal component analysis and entropy weight methods to establish the indexing measurement. *PloS One, 17*(1), e0262261. https://doi.org/10.1371/journal.pone.0262261

Wu, R. M. (2022). Which objective weight method is better: PCA or entropy? *Scientific Journal of Research & Reviews, 3*(3), e000558. https://doi.org/10.33552/SJRR.2022.03.000558

Yadav, V., Karmakar, S., Kalbar, P. P., & Dikshit, A. K. (2019). PyTOPS: A Python based tool for TOPSIS. *SoftwareX, 9*, 217-222. https://doi.org/10.1016/j.softx.2019.02.004

Yadav, P. D., Mohandas, S., Shete, A., Sapkal, G., Deshpande, G., Kumar, A., Wakchaure, K., Dighe, H., Jain, R., Ganneru, B., Yemul, J., Gawande, P., Vadrevu, K. M., & Abraham, P.

(2022). Protective efficacy of COVAXIN® against Delta and Omicron variants in hamster model. *iScience, 25*(10). https://doi.org/10.1016/j.isci.2022.105178

Yang, X., Gajpal, Y., Roy, V., & Appadoo, S. (2022). Tactical level operating theatre scheduling of elective surgeries for maximizing hospital performance. *Computers & Industrial Engineering, 174*, 108799. https://doi.org/10.1016/j.cie.2022.108799

Yung, C. F., Pang, D., Kam, K. Q., Lye, D. C., Ong, B., Chong, C. Y., & Tan, K. B. (2023). BNT162b2 vaccine protection against omicron and effect of previous infection variant and vaccination sequence among children and adolescents in Singapore: a population-based cohort study. *The Lancet Child & Adolescent Health, 7*(7), 463–470. https://doi.org/10.1016/S2352-4642(23)00101-3

Zhao, F., Zai, X., Zhang, Z., Xu, J., & Chen, W. (2022). Challenges and developments in universal vaccine design against SARS-CoV-2 variants. *npj Vaccines, 7*(1), 167. https://doi.org/10.1038/s41541-022-00597-4

Zou, G., Yun, Y., & Sun, J. (2006). Entropy method for determination of weight of evaluating indicators in fuzzy synthetic evaluation for water quality assessment. *Journal of Environmental Sciences, 18*(5), 10201023. https://doi.org/10.1016/S1001-0742(06)60032-6

Zhu, Y., Tian, D., & Yan, F. (2020). Effectiveness of entropy weight method in decision-making. *Mathematical problems in Engineering, 2020*(1), 3564835. https://doi.org/10.1155/2020/3564835

Appendix: Computational Codes

To ensure full transparency and reproducibility, this appendix contains all source code used in the implementation of the methods presented in this thesis. This section covers the three main computational procedures: Shannon entropy weighting, Wen entropy weighting, the TOPSIS ranking process. All scripts are provided in Python, with parallel versions available in Excel for accessibility. The codes are fully annotated to clarify each step of the procedure, enabling independent verification, adaptation, or extension for future research.

A.1 Shannon Entropy Weighting

This script computes criterion weights using the Shannon entropy method. It takes a decision matrix as input, normalizes the data, calculates entropy values for each criterion, and derives weights based on the degree of variability.

```
import numpy as np

def calculate_entropy_weights(D):

    m, n = D.shape

   # Step 1: Normalize the decision matrix
    r = D / D.sum(axis=0)

   # Step 2: Entropy calculation
    E = -np.sum(r * np.log(r), axis=0) / np.log(m)

   # Step 3: Diversification
```

```
    d = 1 - E

  # Step 4: Weights
    w = d / np.sum(d)
    return w
```

A.2 Wen Entropy Weighting

This script implements the Wen entropy method which modifies the entropy formula to provide a more balanced weighting distribution. It prevents low-variance but important criteria from being marginalized.

```
import numpy as np

def we(x):
    """Wen entropy weighting function."""
    return x * np.exp(1 - x) + (1 - x) * np.exp(x) - 1

def normalize_matrix(D, criteria):

    R = np.zeros_like(D, dtype=float)
    for j in range(D.shape[1]):
        if criteria[j] == 'benefit':
            R[:, j] = (D[:, j] - np.min(D[:, j])) / (np.max(D[:, j]) -
               np.min(D[:, j]))
        elif criteria[j] == 'cost':
            R[:, j] = (np.max(D[:, j]) - D[:, j]) / (np.max(D[:, j]) -
               np.min(D[:, j]))
```

```
    return R

def calculate_wen_entropy_weights(D, criteria):

    # Step 1: Normalize the decision matrix
    R = normalize_matrix(D, criteria)
    m, n = R.shape

    # Step 2: Column sums
    D_j = np.sum(R, axis=0) + 1e-10

    # Step 3: Scaling coefficient
    K = 1 / ((np.exp(0.5) - 1) * m)

    # Step 4: Entropy calculation
    e_j = np.zeros(n)
    for j in range(n):
        e_j[j] = K * np.sum(we(R[:, j] / D_j[j]))

    # Step 5: weights
    w = (1 - e_j) / (n - np.sum(e_j))
    w = w / np.sum(w)

    return w
```

A.3 TOPSIS Ranking

This script integrates the calculated weights into the modified TOPSIS framework. It computes the normalized decision matrix, identifies the positive and negative ideal solutions, calculates distances, and produces a final ranking of vaccine alternatives.

```
import numpy as np
import pandas as pd

def topsis(decision_matrix, weights, criteria_type):

    X = np.array(decision_matrix, dtype=float)
    weights = np.array(weights, dtype=float)
    assert np.isclose(np.sum(weights), 1), "Weights must sum to 1."
    m, n = X.shape
    assert n == len(weights) == len(criteria_type)

    # STEP 1: Normalize the decision matrix
    norm = np.sqrt(np.sum(X**2, axis=0))
    R = X / norm

    # STEP 2: Weighted normalized decision matrix
    V = R * weights

    # STEP 3: Determine ideal and negative-ideal solutions
    ideal = np.zeros(n)
    nadir = np.zeros(n)
    for j in range(n):
        if criteria_type[j].lower() == 'benefit':
```

```
            ideal[j] = np.max(V[:, j])
            nadir[j] = np.min(V[:, j])
        elif criteria_type[j].lower() == 'cost':
            ideal[j] = np.min(V[:, j])
            nadir[j] = np.max(V[:, j])
        else:
            raise ValueError("criteria_type elements must be 'benefit'
                or 'cost'")

    # STEP 4: Calculate separation measures
    D_pos = np.sqrt(np.sum((V - ideal)**2, axis=1))
    D_neg = np.sqrt(np.sum((V - nadir)**2, axis=1))

    # STEP 5: Calculate relative closeness
    RC = D_neg / (D_pos + D_neg)

    # STEP 6: Rank alternatives
    rank = np.argsort(-RC)  # Highest RC is best

    return RC, rank
```