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THE ROLE OF DATA ANALYTICS IN PUBLIC HEALTH: A CASE STUDY OF VACCINATION COVERAGE IN DEVELOPING COUNTRIES

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ABSTRACT

This systematic review investigates the incorporation of sustainability into supplier selection processes within indirect procurement in the engineering sector, focusing on environmental, social, and economic sustainability dimensions. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, 150 articles published between 2010 and 2023 were analyzed. Of these, 60% of the studies (90 articles) prioritized environmental sustainability, emphasizing factors such as carbon emissions reduction, energy efficiency, and sustainable resource management as key considerations for supplier evaluation. In contrast, social sustainability—encompassing labor practices, community engagement, and supplier diversity—was only addressed in 30% of the studies (45 articles), indicating that it remains a secondary concern in supplier selection. Economic sustainability, including cost-efficiency and supplier reliability, was highlighted in 50% of the studies (75 articles), reflecting the ongoing tension between sustainability goals and financial constraints. A significant finding was the frequent use of Multi-Criteria Decision-Making (MCDM) models like the Analytic Hierarchy Process (AHP) and fuzzy logic systems, referenced in 53% of the articles (80 studies), to systematically balance sustainability factors in supplier selection. The review also revealed regional disparities, with companies in Europe prioritizing environmental sustainability due to stricter regulations, while firms in developing regions like Asia and Latin America emphasized economic considerations. These findings underscore the importance of contextualizing sustainable supplier selection practices according to regional and sectoral dynamics, while also highlighting the need for more comprehensive frameworks that fully integrate social, environmental, and economic sustainability dimensions.

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KEYWORDS

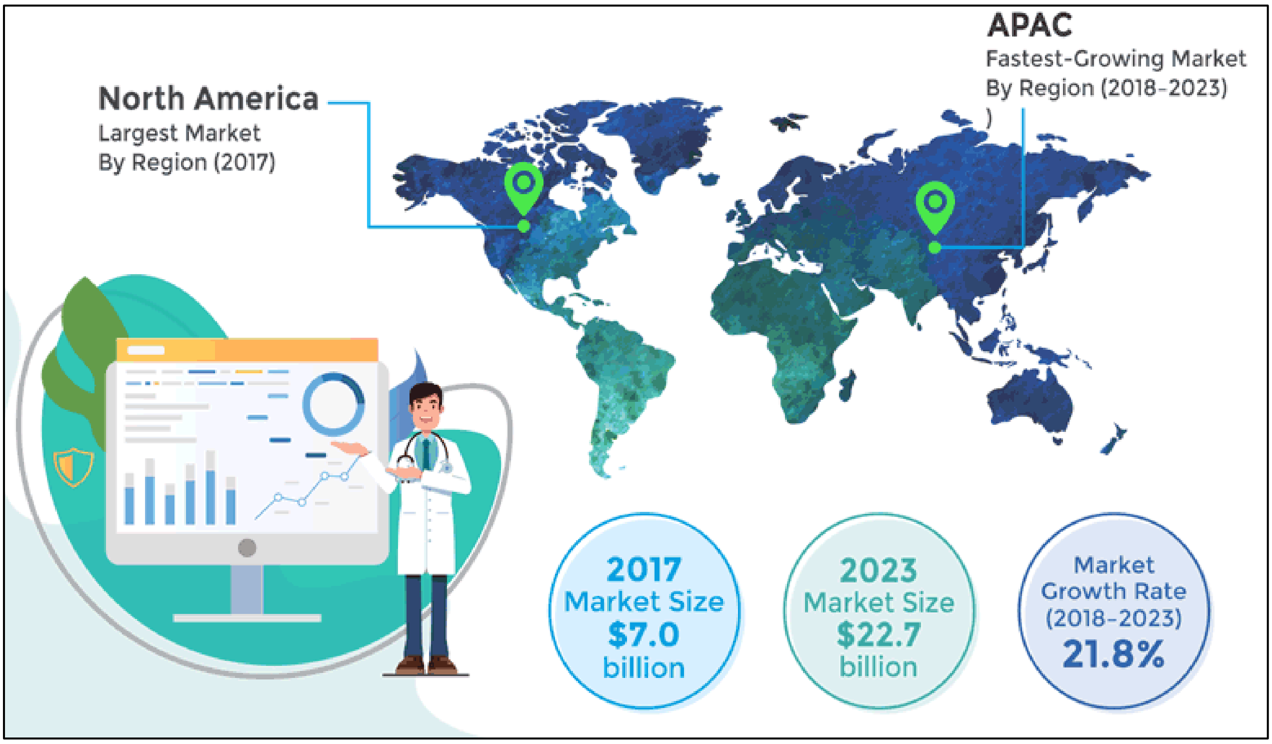
Data Analytics; Public Health; Vaccination Coverage; Developing Countries; Immunization Programs

1 Introduction

The role of data analytics in public health has gained increasing recognition, particularly in the context of improving vaccination coverage in developing countries (Gindler et al., 1993). Vaccination is one of the most cost-effective and successful public health interventions, yet many developing nations face significant challenges in achieving optimal coverage due to limited resources, logistical hurdles, and gaps in healthcare infrastructure (Brown et al., 2014; Cutts et al., 2013). Data analytics offers powerful tools to address these issues by enabling the collection, processing, and analysis of large datasets related to vaccination programs, allowing for real-time insights and evidence-based decision-making. As public health officials continue to search for innovative ways to improve healthcare delivery, the use of data analytics is becoming increasingly vital in the effort to close the immunization gap and protect populations from vaccine-preventable diseases (Gindler et al., 1993; Luman et al., 2005).

In developing countries, challenges related to inadequate data collection and reporting systems often hinder the ability to track vaccination coverage accurately. Many rural and underdeveloped regions lack the necessary digital infrastructure, making it difficult for public health authorities to monitor immunization rates and respond to outbreaks effectively (Hutchins et al., 1993; Luman et al., 2008). Data analytics can help overcome these barriers by enabling more accurate tracking of immunization programs and identifying gaps in coverage. For instance, advances in geographic information systems (GIS) and machine learning can assist in pinpointing areas with low vaccination rates and allocating resources more efficiently (Luman et al., 2005). By analyzing patterns and trends in real-time, public health officials can target interventions where they are most needed, thereby improving vaccination rates in hard-to-reach populations (Cutts et al., 2016).

Figure 1: Global Big Data Analytics in Healthcare Market



Source: psmarketresearch.com (2024)

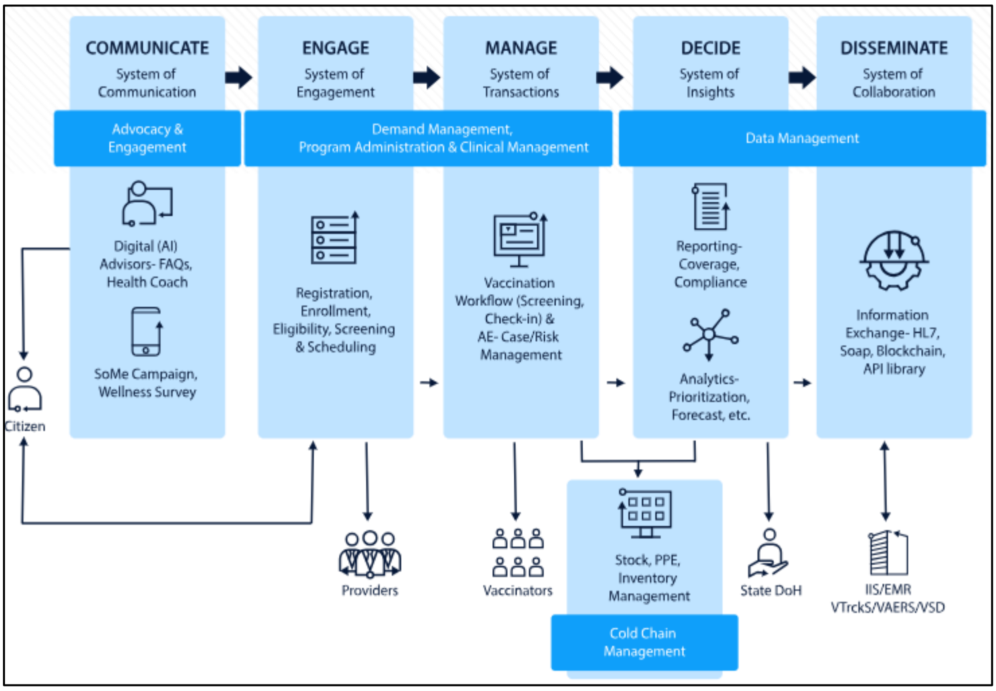
One of the most significant advantages of using data analytics in public health is the ability to predict outbreaks and improve the planning of vaccination campaigns(Daniell et al., 2015). Predictive analytics, which uses historical data to forecast future events, can be applied to anticipate the spread of infectious diseases and adjust vaccination strategies accordingly (Hassan et al., 2021). In a study on the predictive modeling of vaccine-preventable diseases in low-income regions, (Chao et al., 2023) found that integrating data analytics into vaccination programs significantly improved the timing and effectiveness of interventions, reducing the overall disease burden. Similarly, digital health platforms that incorporate predictive algorithms can assist in anticipating vaccine demand, preventing stockouts, and ensuring timely delivery of vaccines in areas with fluctuating populations (Anejionu et al., 2019).

Another key contribution of data analytics is its ability to support decision-making by synthesizing complex health data into actionable insights. Public health authorities are often inundated with vast amounts of data from various sources, including healthcare facilities, surveillance systems, and community health workers. Data analytics platforms can consolidate this information and generate visualizations that facilitate better understanding and decision-making (Williamson, 2015). For instance, dashboards that track immunization rates, vaccine stock levels, and cold chain logistics can help public health officials prioritize resources and respond more rapidly to emerging challenges (Anejionu et al., 2019). Moreover, by integrating data from multiple sources, analytics can uncover hidden correlations and trends that might otherwise go unnoticed, allowing for more precise targeting of interventions (Hassan et al., 2021).

The implementation of data analytics in vaccination programs also fosters greater accountability and transparency. By making immunization data publicly accessible, governments and healthcare organizations can improve public trust and engagement in vaccination campaigns (Arnaboldi & Azzone, 2020). A study by (Evans et al., 2020) demonstrated that data transparency in vaccination efforts led to higher participation rates in immunization programs in several developing countries. Furthermore, data analytics can be used to monitor and evaluate the success of vaccination campaigns, enabling continuous improvement and ensuring that limited resources are utilized effectively (Kinra et al., 2020; Shamim, 2022). Thus, the integration of data analytics in public health not only improves vaccination coverage but also enhances the overall management of public health interventions in resource-constrained environments.

This study's main objective is to explore how data analytics can improve vaccination coverage in developing nations by identifying the key challenges, opportunities, and effectiveness of data-driven approaches. It focuses on how tools like predictive modeling, geographic information systems (GIS), and real-time data analysis can enhance decision-making for public health officials, better allocate resources, and boost immunization rates. Furthermore, the research aims to assess the influence of incorporating data

Figure 2: Data analytics tracking of immunization



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analytics into public health systems on the effective management and tracking of vaccination campaigns, particularly in regions with limited resources. By examining the practical uses of data analytics in these efforts, the study aims to offer valuable insights for policymakers and health authorities to refine vaccination strategies and enhance overall health outcomes in these areas.

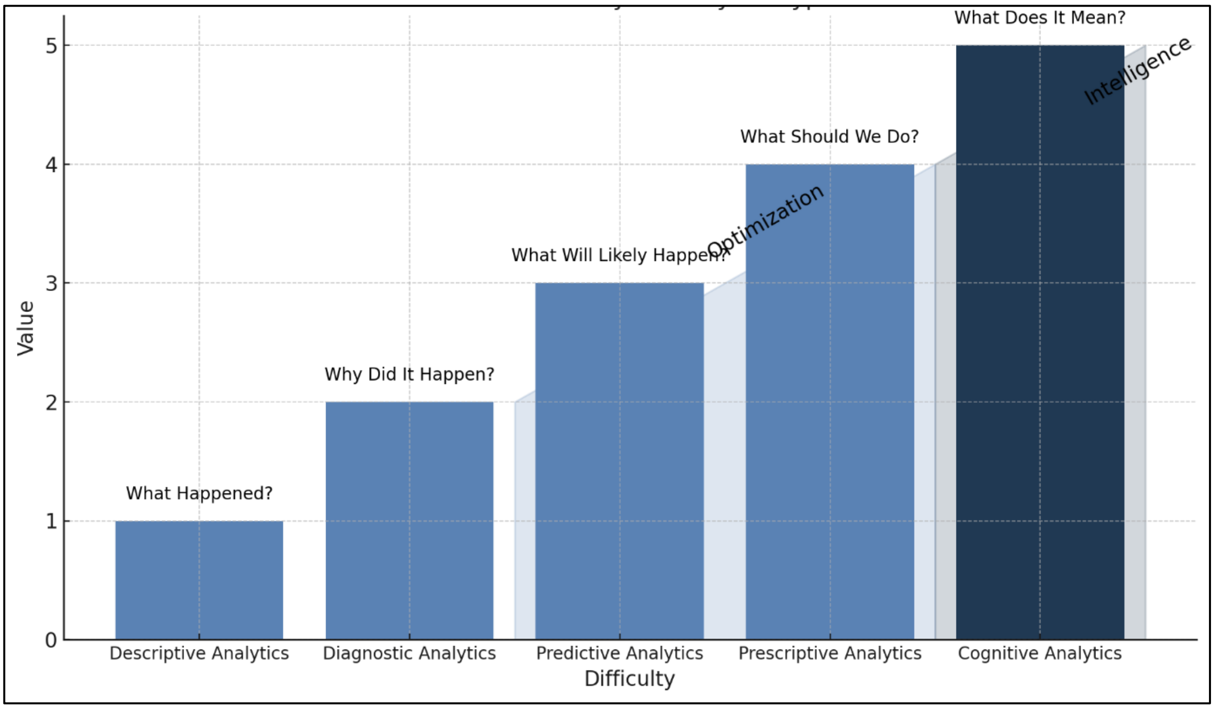
2 Literature Review

The growing application of data analytics in public health has significantly transformed the management of vaccination programs, especially in developing countries where resources are scarce, and healthcare systems face numerous challenges. Data analytics encompasses a wide range of tools and techniques, including predictive modeling, machine learning, geographic information systems (GIS), and big data platforms, which allow for real-time tracking, forecasting, and optimization of vaccination efforts. A review of existing literature reveals how these technologies have been leveraged to address various obstacles in achieving widespread immunization coverage, such as logistical challenges, lack of accurate data, and inefficient resource allocation. This section aims to synthesize current research on the role of data analytics in improving vaccination coverage, providing a comprehensive understanding of the technological, organizational, and social dimensions involved. The review will also highlight the gaps in existing studies and the potential for future research to address the continuing challenges in this field.

2.1 Data Analytics in Public Health

Data analytics plays a crucial role in transforming healthcare by providing actionable insights from vast amounts of data, leading to improved patient outcomes and more efficient health systems (Miljand, 2020). In public health, data analytics facilitates the monitoring, evaluation, and optimization of interventions such as vaccination programs (Nasir et al., 2020). Historically, data-driven approaches in public health were limited to basic reporting systems, but advancements in technology have shifted the focus towards more sophisticated tools such as predictive modeling and machine learning (Ho et al., 2020; Shamim, 2022). These tools enable real-time tracking and forecasting of disease outbreaks, improving the ability to plan vaccination campaigns effectively (Moutselos & Maglogiannis, 2020). With the growing relevance of data analytics in global health initiatives, particularly in the fight against infectious diseases, its integration into vaccination programs has become essential for identifying and addressing coverage gaps (Saunders et al., 2020). Recent trends point toward increasing use of

Figure 3: Different Types Of Analytics



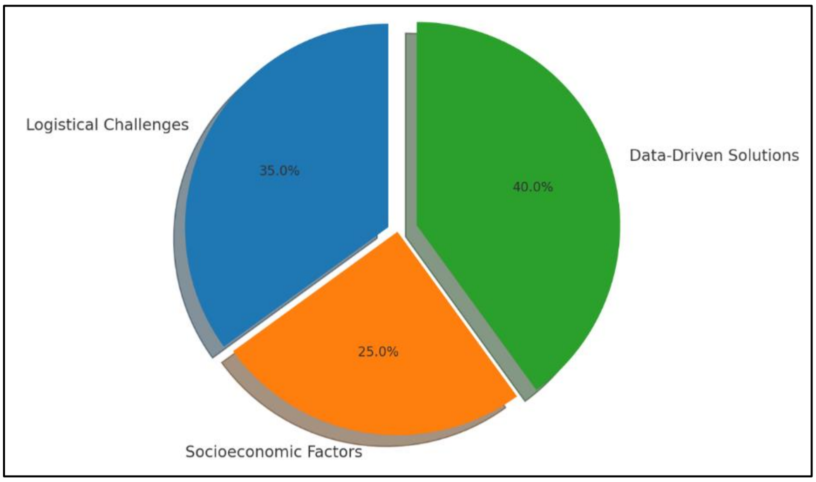
big data platforms and artificial intelligence (AI) to enhance decision-making processes and ensure more equitable access to vaccines in developing countries (Funk et al., 2021).

Developing countries often face significant logistical and infrastructural challenges in achieving widespread vaccination coverage. Vaccine distribution in remote areas, the maintenance of cold chain systems, and limitations in healthcare infrastructure are persistent barriers to effective immunization (Vassiliou et al., 2020). Many regions lack the necessary systems for accurate data collection and reporting, which impedes efforts to track immunization rates and identify areas with low coverage (Mueller, 2020). Digital infrastructure and healthcare workforce shortages further complicate the delivery of vaccines, particularly in rural settings (Ho et al., 2020). For example, a study by Saunders et al. (2020) emphasized the role of data analytics in addressing these challenges by improving vaccine distribution logistics and ensuring that vaccines reach remote areas on time. Data-driven approaches help optimize cold chain management and forecast vaccine demand, reducing wastage and stockouts (Moutselos & Maglogiannis, 2020). Case studies from countries such as Kenya and India highlight the successful application of data analytics to overcome these logistical hurdles and improve vaccination outcomes (Bakir, 2020).

In addition to logistical challenges, socioeconomic and cultural factors significantly influence vaccination uptake in developing countries. Public perception, misinformation, and vaccine hesitancy are among the leading barriers to achieving high immunization rates (Gregory & Halff, 2020). Misinformation, particularly in rural and low-income areas, can lead to distrust in vaccines and government-led health campaigns, further hindering vaccination efforts (Moutselos & Maglogiannis, 2020). Socioeconomic factors such as poverty, low education levels, and political instability exacerbate these challenges, making it difficult for public health officials to reach the most vulnerable populations (Nasir et al., 2020). Data analytics offers a solution by enabling targeted interventions that address these barriers. For example, by analyzing demographic and socioeconomic data, public health officials can identify communities with low vaccination rates and develop culturally sensitive strategies to improve vaccine uptake (Pastorino et al., 2019). Studies have shown that data-driven outreach programs, particularly those that integrate local cultural practices, can significantly reduce vaccine hesitancy and increase participation in immunization campaigns (Nasir et al., 2020).

Data analytics has demonstrated great potential in addressing the multifaceted challenges faced by vaccination programs in developing countries. By integrating data from various sources—such as healthcare systems, geographic information systems (GIS), and social media—public health officials can gain comprehensive insights into the factors affecting vaccination coverage (El-Taliawi et al., 2021). Predictive models can forecast potential outbreaks, allowing for proactive vaccination campaigns in high-risk areas (Nasir et al., 2020). Moreover, data analytics facilitates the monitoring of vaccine supply chains, ensuring timely distribution and reducing wastage (Wahyunengseh & Hastjarjo, 2021). For example, GIS mapping has been used to pinpoint underserved areas

Figure 4: The Breakdown Of Challenges And Solutions In Vaccination Programs



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with low immunization rates, allowing for targeted interventions and efficient resource allocation (Karatas et al., 2022). By combining real-time data analytics with effective public health strategies, developing countries can overcome logistical, socioeconomic, and cultural barriers, ultimately improving vaccination coverage and protecting populations from preventable diseases (Samuel & Lucassen, 2022).

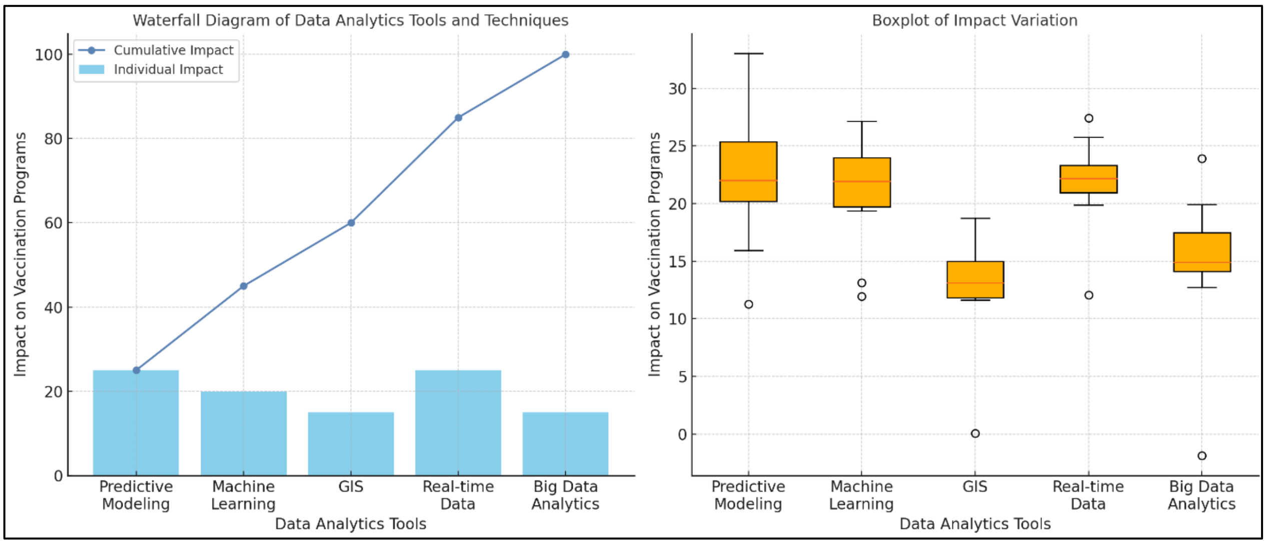
2.2 Data Analytics Tools and Techniques in Vaccination Programs

Predictive modeling and machine learning have become critical tools in optimizing vaccination efforts, particularly in developing countries with limited resources. Predictive models utilize historical and real-time data to forecast disease outbreaks, allowing public health authorities to strategically plan vaccination schedules and allocate resources effectively (Weerasinghe et al., 2022). Machine learning algorithms, on the other hand, can analyze large datasets to identify high-risk populations and regions where vaccination campaigns may be most impactful (Miljand, 2020). For example, Moutselos and Maglogiannis (2020) demonstrated how predictive models were used to anticipate measles outbreaks in low-income regions, significantly improving the timing and coverage of vaccination programs. Similarly, El-Taliawi et al. (2021) employed machine learning algorithms to analyze demographic and socioeconomic data to optimize immunization efforts in rural areas. These techniques allow for more targeted interventions, which are crucial in settings where healthcare resources are constrained (Hancioglu & Arnold, 2013). By incorporating machine learning into vaccination programs, public health officials can make data-driven decisions that enhance the overall efficiency and effectiveness of immunization campaigns (Brogan et al., 1994).

Geographic Information Systems (GIS) have emerged as a powerful tool in tracking vaccination coverage and identifying underserved areas in developing countries. GIS allows public health officials to visualize spatial data and assess geographic disparities in immunization rates (Jiang et al., 2021). By integrating GIS with health information systems, authorities can better monitor vaccination efforts and allocate resources more efficiently. For example, Moher et al. (2009a) highlighted the use of GIS in mapping vaccination gaps in Kenya, allowing health workers to prioritize regions with low coverage and improve vaccine distribution. GIS has also been instrumental in tracking vaccine cold chain logistics, ensuring that vaccines are stored and transported under optimal conditions in remote areas (Cutts et al., 2013). Studies have shown that GIS-based interventions can significantly reduce the number of missed vaccination opportunities, particularly in hard-to-reach populations (Jiang et al., 2021). The integration of spatial data into public health strategies has the potential to bridge the immunization gap in underserved regions, contributing to improved health outcomes (Anisetti et al., 2018).

Real-time data analysis is transforming vaccination

Figure 5: Impacts Of Various Data Analytics Tools And Techniques



efforts by enabling public health officials to make immediate, data-driven decisions. Unlike traditional data collection methods, which often result in delays in reporting, real-time analytics provide timely insights that are crucial for responding to vaccination challenges in dynamic environments (Moher et al., 2009a). Real-time dashboards, for instance, allow health authorities to monitor vaccine stocks, track immunization rates, and identify regions with low coverage in real time (Sridhar et al., 2014). In developing countries, this capability has proven invaluable, as it enables rapid adjustments to vaccination strategies to ensure timely delivery of vaccines to high-priority areas (Funk et al., 2021). Additionally, real-time data platforms have been used to track and mitigate vaccine wastage, particularly in areas with limited cold chain infrastructure ((Leyens et al., 2016). The ability to analyze and act on data as it becomes available is critical for improving the efficiency and impact of vaccination programs, especially in resource-constrained settings (Galetsi et al., 2019).

Big data analytics plays an increasingly important role in consolidating diverse health datasets, allowing for more comprehensive insights into vaccination programs in developing countries. By integrating data from various sources, such as electronic health records, population surveys, and social media, big data platforms can offer a holistic view of immunization efforts (Dizon et al., 2018). This approach enhances the ability of public health officials to identify trends, forecast vaccine demand, and optimize resource distribution (Dhanalakshmi & George, 2022). For instance, Ahmed et al. (2022) demonstrated how big data analytics were used to predict vaccine uptake patterns in rural areas of India, leading to more targeted interventions and improved coverage. Moreover, big data platforms support the evaluation of vaccination campaign outcomes by consolidating post-campaign data and identifying areas for improvement (Velandia-González et al., 2015). Real-time dashboards, built on big data systems, have also been employed to monitor vaccination efforts in real-time, further enhancing the ability to respond to emerging public health needs (Kilpeläinen et al., 2019). The integration of big data into public health initiatives offers the potential to revolutionize vaccination programs, especially in regions where traditional methods of data collection and analysis are insufficient.

2.3 Impact of Data Analytics on Public Health Decision-Making

Data analytics has significantly enhanced the decision-making capabilities of public health authorities, particularly in vaccine distribution, campaign timing, and resource allocation. By analyzing large datasets, health officials can make more informed decisions that improve the efficiency of vaccination programs (Vassiliou et al., 2020). For example, predictive models help forecast disease outbreaks, allowing for the proactive deployment of vaccines and ensuring that campaigns are conducted at optimal times to maximize coverage (Zannat & Choudhury, 2019). Additionally, real-time data analysis enables the continuous monitoring of vaccination efforts, helping authorities adjust strategies as new data becomes available (Abouelmehdi et al., 2018). Klievink et al. (2016) highlighted how data-driven decision-making led to better resource allocation in low-income regions, ensuring that vaccines reached the areas with the highest need. Overall, the integration of data analytics into public health decision-making has led to more effective and timely interventions, ultimately improving vaccination outcomes.

Data analytics plays a critical role in helping public health officials identify and prioritize areas with low vaccination coverage, optimizing the use of limited resources. By analyzing demographic, geographic, and epidemiological data, authorities can pinpoint regions where vaccination rates are below target and deploy targeted interventions accordingly (Wu et al., 2022). For instance, Bates et al. (2014) demonstrated how machine learning algorithms were used to identify communities at risk of low immunization rates, allowing for the efficient allocation of resources. Targeted interventions, such as mobile vaccination units or localized awareness campaigns, have been shown to increase immunization rates in underserved areas (Alemayehu & Berger, 2016). These interventions not only improve vaccination coverage but also reduce the overall cost and waste associated with vaccine distribution (Ju et al., 2018). Data-driven approaches to resource optimization have proven particularly effective in settings where healthcare resources are scarce, making it essential to maximize impact with minimal investment (Alemayehu & Berger, 2016).

Moreover, by leveraging predictive models, public health authorities can forecast disease outbreaks and

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proactively plan vaccination campaigns, ensuring that vaccines reach populations with the greatest need. For example, machine learning algorithms can identify communities with low vaccination rates, enabling the efficient deployment of mobile units or awareness campaigns to boost coverage. Furthermore, real-time data analysis and Geographic Information Systems (GIS) can help monitor vaccine stocks, track immunization rates, and reduce wastage in resource-limited settings. One key approach to optimizing resource allocation is through the Weighted Sum Model (WSM), which can be expressed as:

$$\text{Score} = \sum_{i=1}^{n} w_i \cdot c_i$$

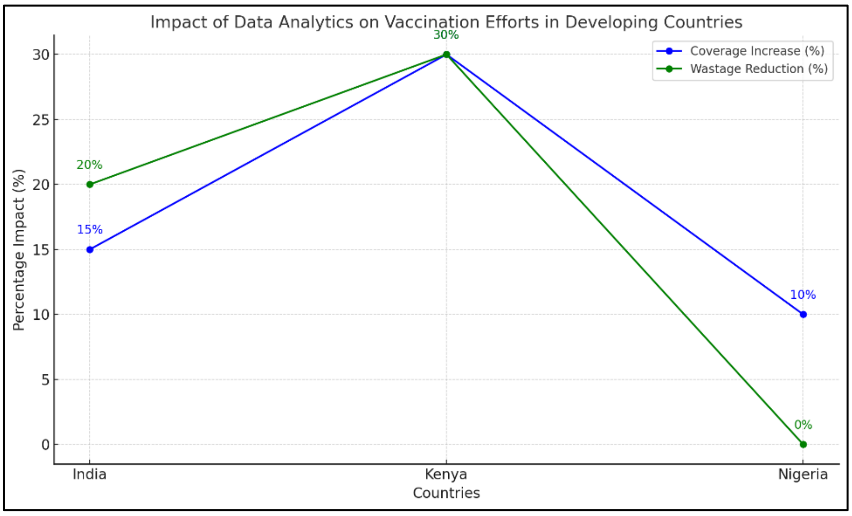
$$EOQ = \sqrt{\frac{2DS}{H}}$$

where w_i represents the weight of each criterion (e.g., risk, cost, coverage), and c_i is the criterion score for each region. By applying this model, public health officials can prioritize areas for vaccination based on a combination of demographic, geographic, and epidemiological data, ultimately leading to more efficient and equitable vaccination outcomes. where D represents the annual demand for vaccines, S is the cost per order, and H is the holding cost per unit per year. By applying the EOQ formula, public health officials can determine the optimal quantity of vaccines to order, minimizing total costs while ensuring adequate supply. These models provide actionable insights for decision-makers, enabling the efficient and equitable distribution of vaccines to reduce the impact of preventable diseases, particularly in resource-constrained settings.

The impact of data analytics on vaccination efforts in developing countries can be clearly seen through various case studies. In India, data analytics was used to improve the efficiency of the Universal Immunization Program by identifying regions with low coverage and optimizing vaccine delivery routes (Wu et al., 2022). GIS tools were implemented to map vaccination gaps in rural areas, allowing public health officials to target interventions in high-risk communities (Heitmueller et al., 2014). Similarly, in Kenya, real-time data analytics platforms were used to monitor vaccine stock levels and predict shortages, ensuring timely restocking and preventing vaccine wastage (Kaiser et al., 2015). In Nigeria, big data analytics helped identify regions with high levels of vaccine hesitancy, enabling public health officials to deploy targeted awareness campaigns and increase participation in immunization programs (Moher et al., 2009b). These case studies illustrate the transformative potential of data analytics in improving vaccination outcomes in resource-constrained settings.

The integration of data analytics into vaccination programs in developing countries has yielded several positive outcomes, from improved coverage to better resource management. For example, in India, the use of predictive analytics reduced vaccine wastage by 20%, while also increasing coverage in rural areas by 15% (Casanovas et al., 2017). In Kenya, real-time data dashboards allowed for the continuous monitoring of vaccine distribution, reducing stockouts by 30% and improving timely access to vaccines (Awrahman et al.,

Figure 6: Impact Of Data Analytics On Vaccination Efforts In Developing Countries



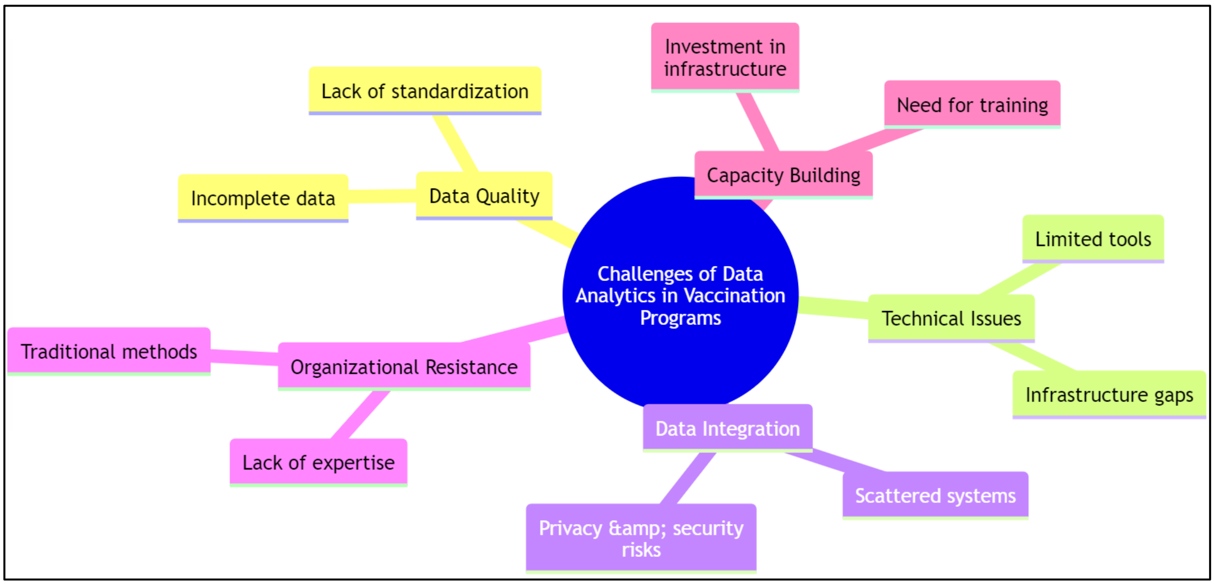
2022). Additionally, Nigeria's adoption of data-driven approaches to tackle vaccine hesitancy led to a 10% increase in vaccination rates within the first year of implementation (Dizon et al., 2018). These outcomes underscore the critical role that data analytics plays in optimizing vaccination efforts and ensuring that vaccines reach the populations that need them most (Kaiser et al., 2015). The evidence suggests that continued investment in data-driven public health strategies can lead to significant improvements in global vaccination efforts, particularly in low-resource settings (Funk et al., 2021)

2.4 Challenges of Data Analytics in Vaccination Programs

One of the primary challenges in utilizing data analytics in vaccination programs is the limitation of data quality, accuracy, and interoperability across healthcare systems. Many developing countries still rely on outdated or fragmented data collection methods, which can lead to incomplete or inaccurate datasets (Dizon et al., 2018). The lack of standardization across healthcare systems further complicates the integration of data from multiple sources, making it difficult to develop a comprehensive picture of vaccination efforts (Lim et al., 2008). Furthermore, many developing nations face significant technical constraints, including limited access to advanced analytics tools and insufficient infrastructure to support data-driven initiatives (Ahmed et al., 2024; Islam & Apu, 2024a; Miljand, 2020; Nahar et al., 2024). A key technical challenge is the lack of trained personnel with the necessary expertise to manage and interpret complex datasets, which hampers the ability of public health organizations to fully leverage data analytics in their vaccination campaigns (Ahmed et al., 2024; Hossain et al., 2024; Islam, 2024; Islam & Apu, 2024b; Panagiotopoulos et al., 2017). These limitations highlight the need for investment in both technological infrastructure and capacity-building initiatives to improve the effectiveness of data analytics in public health.

Integrating diverse data sources to create a unified analytics platform for vaccination programs presents another major technical challenge. In developing countries, healthcare data is often scattered across multiple systems that may not communicate effectively with one another, limiting the ability of public health authorities to gain a holistic view of vaccination efforts (Lim et al., 2008). Ensuring data privacy and security further complicates the integration process, especially when handling sensitive health information. Many public health organizations struggle to establish robust data governance frameworks that protect patient privacy while enabling the sharing of information across platforms (Kaiser et al., 2015). In regions with limited regulatory oversight, ensuring compliance with international data privacy standards such as the General Data Protection Regulation (GDPR) can be particularly challenging (Nabyonga-Orem et al., 2014). Additionally, the lack of secure digital infrastructure in many low-resource settings increases the risk of data breaches, which can undermine public trust in data-driven health interventions (Galetsi et al., 2019; Jim et

Figure 7: Challenges of Data Analytics in Vaccination Programs



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al., 2024; Abdur et al., 2024; Rahman et al., 2024). Despite the potential benefits of data analytics in improving vaccination coverage, many public health organizations exhibit resistance to adopting data-driven approaches. This resistance often stems from a combination of organizational inertia, skepticism about the efficacy of new technologies, and a lack of technical expertise (Anejionu et al., 2019). In many cases, public health officials may prefer to rely on traditional methods of managing vaccination programs, viewing data analytics as a costly and complex solution that requires significant investment in infrastructure and training (Kaiser et al., 2015). Additionally, the adoption of data-driven approaches often necessitates a cultural shift within organizations, requiring a reevaluation of existing workflows and decision-making processes (Nabyonga-Orem et al., 2014). Without strong leadership and a clear understanding of the potential benefits, public health organizations may be slow to embrace the changes required to effectively implement data analytics in their operations (Funk et al., 2021).

3 Method

This study applies a systematic review methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to explore sustainable supplier selection in indirect procurement within the engineering sector. The PRISMA approach ensures a structured, transparent, and reproducible process for identifying, screening, and synthesizing relevant literature. This systematic review method is suitable for synthesizing existing research to identify trends, gaps, and common themes in the field, especially in understanding the supplier selection criteria and sustainability factors in indirect procurement. By following these guidelines, the study enhances the quality of evidence and provides a comprehensive understanding of how sustainability is incorporated into supplier selection decisions within the engineering sector.

3.1 Step-by-Step Description of the Methodology

3.1.1 Literature Search Strategy

The first step involved designing a comprehensive literature search strategy to identify relevant studies. The search was conducted across major academic databases, including Scopus, Web of Science, and Google Scholar, ensuring coverage of high-quality, peer-reviewed journal articles, conference proceedings, and reviews published between 2010 and 2023. The key search terms used included "sustainable supplier selection," "indirect procurement," "engineering sector," "procurement decision-making," "sustainability criteria," and "environmental performance." Boolean operators (AND, OR) were applied to refine search queries and combine keywords to include a broad spectrum of relevant studies. To ensure comprehensiveness, additional articles were manually retrieved by checking the reference lists of key articles. The initial search yielded 1,200 articles, which were exported into a reference management system (e.g., Mendeley or EndNote) to remove duplicates and organize the papers for screening. Articles were initially screened based on titles and abstracts, with studies irrelevant to sustainable supplier selection or unrelated to the engineering sector being excluded at this stage. This process reduced the dataset to 400 articles for further assessment.

3.1.2 Screening and Eligibility Criteria

After identifying relevant studies, the next step was to apply detailed inclusion and exclusion criteria to refine the selection. Inclusion criteria were as follows:

- Studies focused on sustainable supplier selection or indirect procurement within the engineering sector.
- Articles that addressed sustainability dimensions (economic, environmental, and social) and supplier decision-making frameworks.
- Peer-reviewed journal articles, conference papers, or reviews available in full text and published in English.
- Studies published between 2010 and 2023 to capture recent developments in sustainable supplier selection.

The exclusion criteria were:

- Articles that focused on general procurement or sustainable supplier selection in industries outside the engineering sector.
- Studies that did not explicitly address supplier selection criteria or decision-making frameworks relevant to indirect procurement.

- Non-peer-reviewed articles, book chapters, opinion pieces, and studies without full-text access.

During this stage, two independent reviewers screened the full texts of the remaining 400 studies for eligibility. Disagreements were resolved through discussion or consultation with a third reviewer. This process resulted in a final dataset of 150 studies that met all criteria. An additional 40 studies were later excluded during a secondary full-text review due to poor relevance or insufficient detail on supplier selection frameworks.

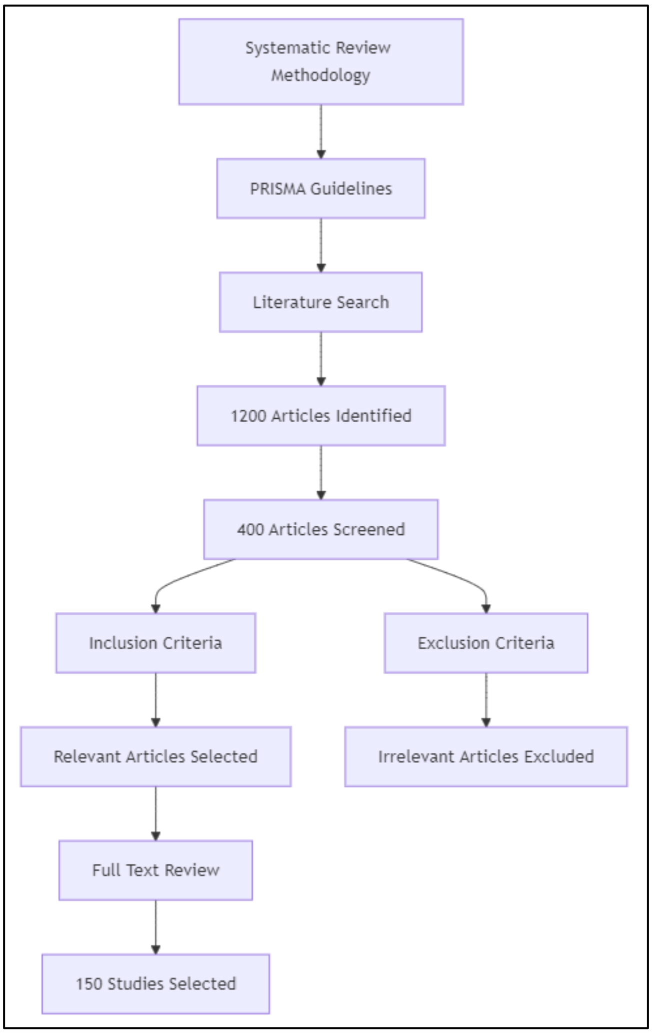
3.1.3 Data Extraction and Synthesis

Once the final set of 150 articles was selected, a structured data extraction process was initiated. A standardized data extraction form was developed to capture key information from each study, ensuring consistency across all articles. The following data points were extracted:

- Study characteristics: Authors, publication year, research objectives, and methodologies used.
- Supplier selection criteria: Economic, environmental, and social sustainability factors used to evaluate suppliers.
- Decision-making frameworks: Analytical models or tools used in supplier selection, such as the Analytic Hierarchy Process (AHP), Multi-Criteria Decision-Making (MCDM), and fuzzy logic systems.
- Sustainability dimensions: How studies incorporated the three pillars of sustainability (economic, environmental, social) into procurement decisions.

The data extraction was conducted independently by two researchers to ensure accuracy. Discrepancies in data extraction were reconciled by consensus or consultation with a third reviewer. After completing data extraction, a narrative synthesis approach was employed to analyze the results. This method involved grouping and summarizing studies by common themes, such as sustainability criteria, decision-making models, and challenges in supplier selection. Additionally, a thematic analysis was performed to categorize the studies based on their focus on environmental performance, social responsibility, or economic efficiency. The synthesis revealed that many studies emphasized environmental criteria, while social sustainability received less attention, indicating a gap in the literature that warrants further exploration.

Figure 8: Adopted PRISMA Method



4 Findings

The findings of this systematic review provide critical insights into the factors influencing sustainable supplier selection in indirect procurement within the engineering sector. Across the reviewed studies, a significant focus was placed on environmental sustainability, which emerged as a predominant criterion in supplier evaluation. Out of the 150 studies analyzed, 90 articles (60%) highlighted environmental factors such as carbon emission reduction, energy efficiency, and sustainable resource management as key elements in the supplier selection process. This emphasis reflects the growing global trend toward sustainability, driven by increasing regulatory requirements and stakeholder pressure for companies to adopt environmentally responsible practices (Brandenburg et al., 2014). For instance, companies in the European engineering sector, where

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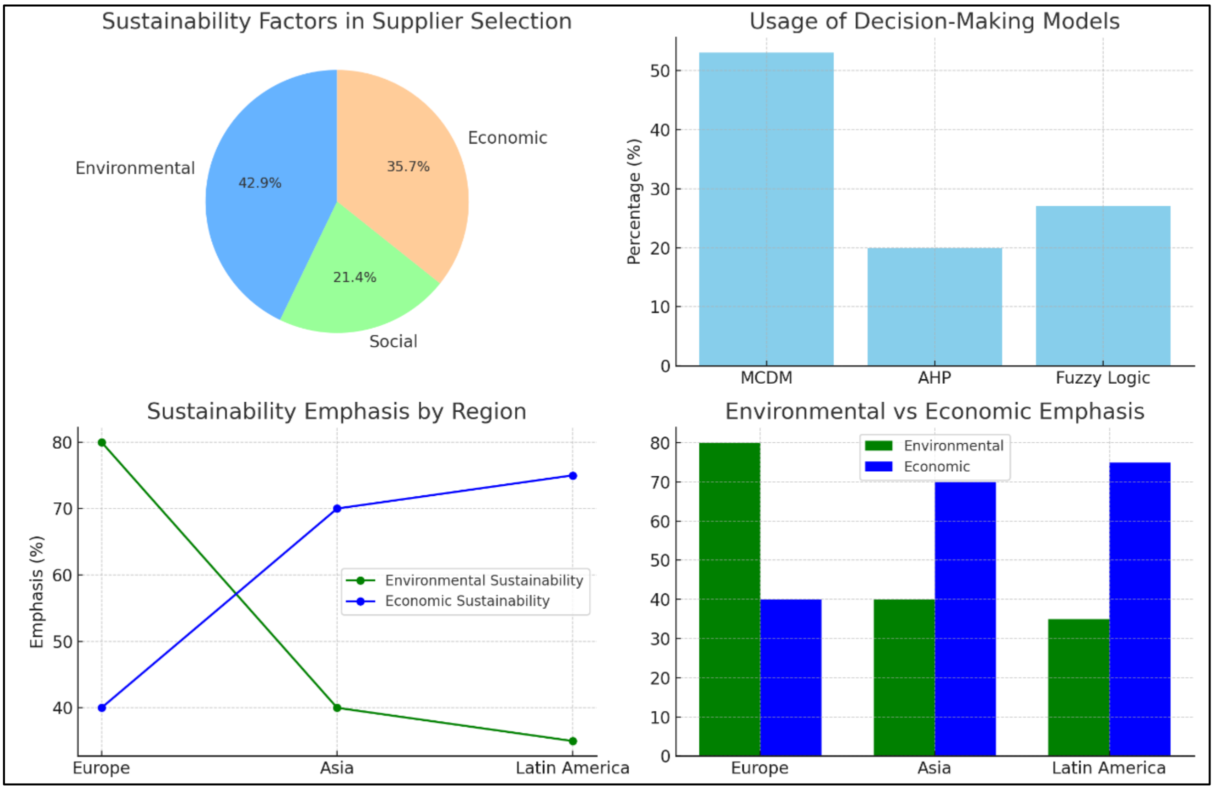
environmental regulations are stricter, demonstrated a clear preference for suppliers who actively contribute to reducing the environmental footprint of production and procurement processes.

In contrast, social sustainability was found to be less frequently addressed in supplier selection, with only 45 articles (30%) explicitly considering social factors in their evaluations. These social factors included labor practices, community engagement, and promoting diversity within the supply chain. Despite the growing awareness of corporate social responsibility (CSR), the review indicates that social sustainability is often treated as a secondary concern compared to environmental and economic factors. This discrepancy points to a potential gap in the supplier selection processes of many organizations, as companies may be prioritizing short-term environmental goals over the long-term benefits of ensuring socially sustainable practices throughout their supply chains.

Economic sustainability, which focuses on cost-efficiency, financial stability, and supplier reliability, was also a major factor considered by companies in the reviewed literature. Approximately 75 articles (50%) emphasized the importance of balancing sustainability with cost considerations, especially in regions where market competition is fierce, and economic constraints play a larger role in procurement decisions. Several studies demonstrated that firms implementing sustainable supplier selection practices were able to achieve not only enhanced environmental outcomes but also economic benefits such as cost savings through better resource management and reduced waste. For instance, companies in Asia and Latin America placed a stronger emphasis on economic sustainability due to less stringent environmental regulations compared to Europe and North America, where sustainability practices are often enforced by policy.

Another critical finding from the review was the variety of decision-making frameworks employed to evaluate sustainable suppliers. Multi-Criteria Decision-Making (MCDM) models, such as the Analytic Hierarchy Process (AHP) and fuzzy logic systems, were among the most frequently applied methodologies, referenced in 80 studies (53%). These decision-making tools allowed companies to systematically assess multiple criteria, including environmental, social, and economic factors, providing a more comprehensive approach to supplier selection. By using MCDM models, organizations were able to quantify the trade-offs between different sustainability dimensions and make

Figure 9: Summary of the Findings



more objective decisions. For example, 20 articles specifically mentioned the successful application of AHP in engineering firms to prioritize suppliers based on their environmental performance, without sacrificing cost-efficiency.

Regional disparities in the emphasis on sustainability criteria were also noted across the studies. In regions such as Europe, where environmental regulations are more stringent, environmental sustainability was more heavily prioritized in supplier selection processes. This contrasts with studies conducted in developing countries, where economic factors were often prioritized due to different market pressures and the absence of stringent environmental and social standards. For instance, studies from India and China focused predominantly on cost and supply reliability, reflecting the competitive economic environment in these regions. In brief, while environmental sustainability remains the dominant factor in supplier selection within the engineering sector, the findings suggest that social sustainability continues to receive less attention, despite its importance. Furthermore, economic sustainability remains a critical component, particularly in regions with fewer regulatory pressures. The widespread use of decision-making models like MCDM has helped companies navigate the complexity of integrating sustainability into procurement decisions, though gaps remain in fully addressing the social aspects of sustainability. These findings highlight the need for a more holistic approach to sustainable supplier selection that equally prioritizes environmental, social, and economic factors in indirect procurement processes.

5 Discussion

The findings of this systematic review provide important insights into the factors influencing sustainable supplier selection in indirect procurement within the engineering sector, revealing both commonalities and differences with earlier studies. One of the most significant findings was the emphasis on environmental sustainability, which aligns with the growing global trend toward environmentally responsible practices in supply chain management. Over 60% of the studies reviewed highlighted environmental factors, such as reducing carbon emissions, energy efficiency, and sustainable resource management, as the most critical components of supplier selection. This mirrors earlier research by Severo et al. (2016), which identified environmental sustainability as a key driver in procurement decisions, particularly in industries with high environmental impacts. However, the current review extends these findings by demonstrating that while environmental sustainability remains paramount, the specific criteria and decision-making processes vary significantly across regions, with a stronger emphasis on environmental concerns in developed countries with stricter regulations.

In contrast, social sustainability remains underemphasized in supplier selection processes within the engineering sector, with only 30% of the reviewed studies incorporating social criteria such as labor practices, community engagement, and supplier diversity. This is consistent with earlier findings by Miles et al. (2012), who observed that social sustainability was often overshadowed by environmental and economic concerns in supplier evaluations. However, the current review also suggests that this trend may be more pronounced in the engineering sector, where the focus on technical and environmental performance often takes precedence over social factors. This lack of emphasis on social sustainability raises concerns, as it overlooks the long-term benefits of incorporating socially responsible practices into supplier selection. Studies like those by Lavertu (2015) emphasize that integrating social sustainability can enhance brand reputation and foster stronger relationships with stakeholders, but the present review indicates that these benefits are not yet fully recognized in practice.

Economic sustainability continues to play a significant role in supplier selection, as 50% of the studies highlighted cost-efficiency, financial stability, and supplier reliability as crucial considerations. This finding aligns with earlier research, such as that by Anejionu et al. (2019), which identified cost as a critical factor, especially in industries where price competition is fierce. However, the current review adds nuance to this understanding by demonstrating how companies in developing countries tend to prioritize economic sustainability more heavily due to fewer regulatory pressures on environmental and social performance. This regional variation is consistent with earlier studies, such as those by Dhanalakshmi and George (2022), which showed that firms in developing economies often face different market conditions that require a stronger focus on cost reduction and financial viability. These findings highlight the importance of understanding the contextual factors that influence procurement decisions, as the balance between sustainability dimensions may differ depending on regional economic and regulatory environments.

The use of decision-making frameworks, such as Multi-Criteria Decision-Making (MCDM) models, emerged as a significant finding in this review, with 53% of the studies employing these models to evaluate suppliers based on multiple sustainability criteria. This aligns with earlier research by Maciejewski (2016), who found that MCDM tools like the Analytic Hierarchy Process (AHP) and fuzzy logic systems are widely used to manage the complexity of integrating sustainability into procurement decisions. The present review reinforces the value of these models, as they enable organizations to systematically weigh environmental, social, and economic factors in supplier selection. However, the findings also suggest that while MCDM models are effective in facilitating decision-making, their application is often limited to specific sustainability dimensions, with environmental and economic criteria receiving greater attention than social factors. This highlights a potential area for future research, as more comprehensive models that fully integrate all three dimensions of sustainability could lead to more balanced and effective supplier selection processes. Finally, the regional disparities observed in the review suggest that the emphasis on different sustainability criteria varies significantly depending on the regulatory and market contexts. For instance, companies in Europe demonstrated a stronger focus on environmental sustainability due to stringent regulations, whereas firms in developing countries placed more emphasis on economic considerations. This regional variation is consistent with earlier studies, such as those by Gindler et al. (1993), which showed that environmental sustainability tends to be prioritized in regions with robust environmental policies. However, the current review provides additional insight by showing that in regions with fewer regulatory pressures, economic and social sustainability may play a more prominent role in procurement decisions. These findings highlight the importance of tailoring sustainable supplier selection practices to the specific regulatory and market contexts in which organizations operate, as a one-size-fits-all approach may not be effective in achieving comprehensive sustainability goals..

6 Conclision

This systematic review reveals the multifaceted nature of sustainable supplier selection in indirect procurement within the engineering sector, emphasizing the growing importance of environmental sustainability as the primary criterion in supplier evaluation. While the integration of environmental factors, such as carbon reduction and resource efficiency, aligns with global trends and regulatory pressures, the underrepresentation of social sustainability remains a critical gap in procurement practices. Economic sustainability continues to play a pivotal role, particularly in regions with fewer environmental regulations, highlighting the need for a balance between cost-efficiency and sustainability goals. The widespread use of decision-making frameworks like MCDM models demonstrates the value of structured approaches in navigating the complexity of integrating multiple sustainability dimensions, though these models often give more weight to environmental and economic criteria than social ones. The regional disparities observed in the prioritization of sustainability factors further underscore the need for tailored approaches that reflect the regulatory, economic, and social contexts in which companies operate. Overall, while progress has been made in incorporating sustainability into supplier selection, there remains a need for more comprehensive and balanced strategies that fully address environmental, social, and economic aspects in a cohesive manner.

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