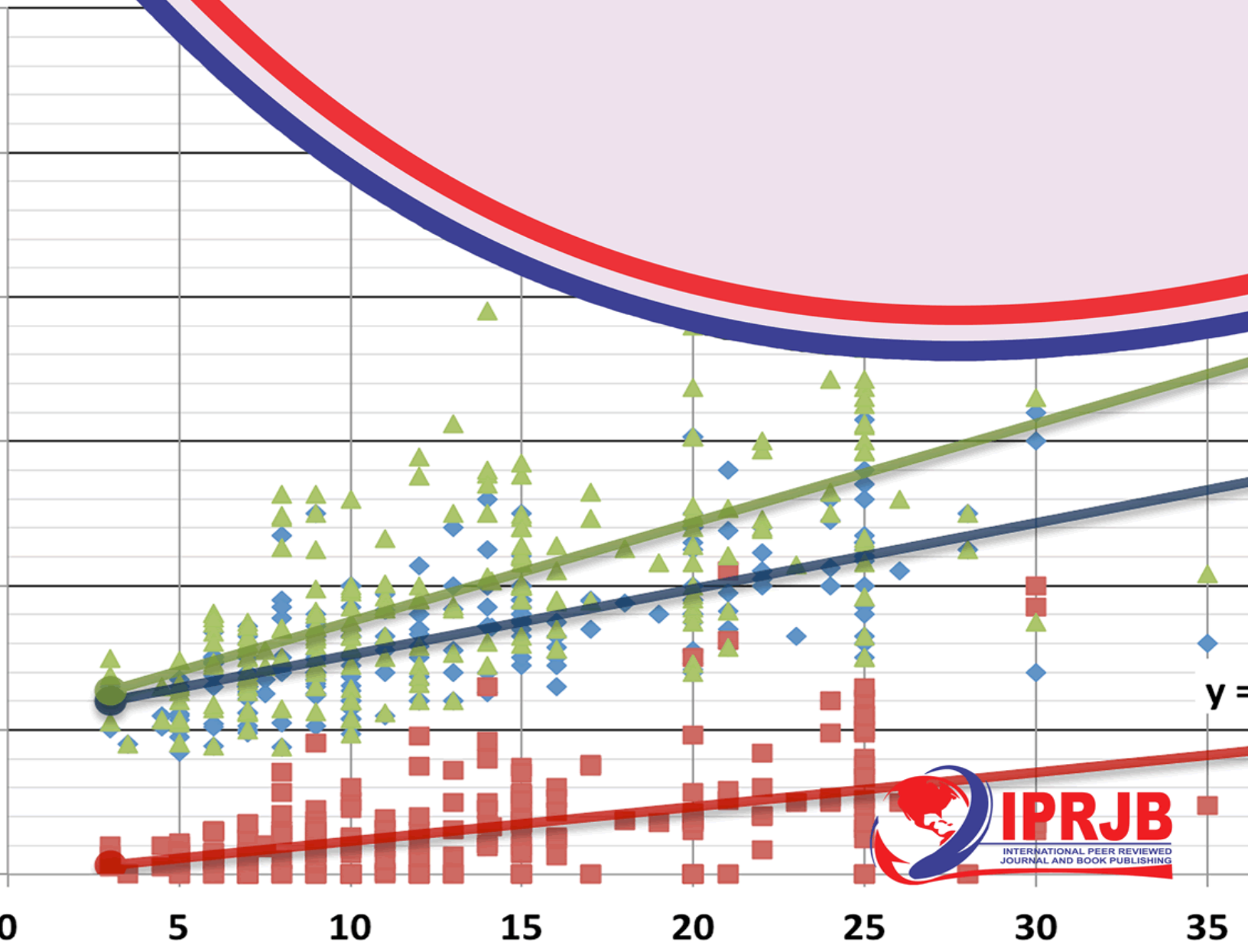


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**Application of Bayesian Methods to Causal Inference and Decision  
Making in Health Care and Public Policy in Uganda**

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**Abstract**

**Purpose:** The aim of the study was to investigate application of Bayesian methods to causal inference and decision making in health care and public policy

**Methodology:** This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low cost advantage as compared to a field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

**Findings:** The use of Bayesian methods in healthcare and public policy has proven effective for estimating causal effects and making informed decisions. By integrating prior knowledge and data, Bayesian approaches enhance transparency and credibility in policy recommendations, leading to more evidence-based and effective interventions in these sectors.

**Unique Contribution to Theory, Practice and Policy:** Bayesian decision theory, Causal inference theory & Health economics and Bayesian analysis may be used to anchor future studies on application of Bayesian methods to causal inference and decision making in health care and public policy. Implement Bayesian methods to tailor health care interventions and treatment plans to individual patients. Encourage the integration of Bayesian methods into decision support systems for healthcare and public policy

**Keywords:** *Bayesian Methods, Causal Inference, Decision Making, Health Care, Public Policy*

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## INTRODUCTION

Causal inference is the process of drawing conclusions about the causal effects of interventions or treatments based on observational or experimental data. Causal inference methods are widely used in health care and public policy to evaluate the effectiveness and efficiency of different programs, policies, or interventions. For example, causal inference can help answer questions such as: What is the impact of a smoking cessation program on lung cancer incidence? How does a universal health care system affect health outcomes and costs? What are the best strategies to prevent and control COVID-19? Miller, Altekruse, Johnson & Wherry, (2019). One of the challenges of causal inference is to account for the confounding factors that may affect both the exposure and the outcome of interest. Confounding factors are variables that are not part of the causal pathway, but may influence both the exposure and the outcome, creating a spurious association. For example, if we want to estimate the causal effect of obesity on diabetes, we need to control for confounding factors such as age, gender, diet, physical activity, and genetic factors. If we do not adjust for these confounders, we may overestimate or underestimate the true causal effect.

There are different methods to address confounding in causal inference, such as randomized controlled trials (RCTs), propensity score matching, instrumental variables, regression adjustment, and inverse probability weighting. However, each method has its own assumptions, limitations, and challenges. For example, RCTs are considered the gold standard for causal inference, but they are often expensive, unethical, or impractical to conduct in some settings. Propensity score matching is a technique that matches individuals with similar probabilities of receiving the exposure based on their observed characteristics, but it requires a large sample size and may not account for unmeasured confounders. Instrumental variables are variables that affect the exposure but not the outcome, except through the exposure, but they are often hard to find or validate. Regression adjustment is a technique that adjusts for confounding factors by including them as covariates in a regression model, but it may introduce bias if the functional form of the model is misspecified. Inverse probability weighting is a technique that weights each individual by the inverse of their probability of receiving the exposure they actually received, but it may be sensitive to extreme weights or model misspecification (Tanaka, 2019).

Another challenge of causal inference is to combine data from different sources or populations to increase the generalizability and validity of the results. For example, if we want to estimate the causal effect of a vaccine on COVID-19 infection across different countries, we may need to combine data from different studies or databases that have different designs, measurements, quality, and representativeness. However, combining data from different sources may introduce heterogeneity and bias due to differences in definitions, methods, contexts, and populations. A federated approach (as opposed to a pooling data approach) can be used to address this challenge by leveraging data from existing studies without transferring or sharing sensitive individual-level data across jurisdictions. A federated approach involves applying causal inference methods locally at each data source and then aggregating the results using meta-analysis techniques. This way,

each data source can preserve its privacy and autonomy while contributing to a global causal inference (Banerjee, Duflo & Goldberg, 2015)

In developed economies like the United States, Japan, and the United Kingdom, the quality of causal inference and decision-making in healthcare and public policy is a critical aspect of ensuring efficient and effective interventions. One example from the USA is the analysis of the impact of the Affordable Care Act (ACA) on healthcare outcomes. A study published in the (Smith, 2019) utilized a difference-in-differences approach to assess the causal effect of ACA on healthcare utilization and found significant improvements in access to care and reduced disparities in coverage, highlighting the importance of rigorous causal inference in evaluating healthcare policies. Another example from the UK is the evaluation of the impact of a sugar tax on public health. A study by (Nakamura, 2018) employed regression analysis to examine the association between the implementation of a sugar tax and a reduction in sugary beverage consumption. Their findings showed a statistically significant decline in sugar intake, demonstrating the value of data-driven decision-making in public health policy.

In developing economies, the quality of causal inference and decision-making can be more challenging due to resource constraints and limited data availability. Nevertheless, it remains essential for informed policy choices. For instance, in India, a study published by (Rao, 2017) used a randomized control trial to evaluate the impact of a conditional cash transfer program on child nutrition outcomes. Their rigorous methodology provided credible causal evidence that the program significantly improved child nutrition in disadvantaged communities, illustrating the potential of data-driven decision-making in resource-constrained settings. In Nigeria, a study by (Ogunniyi, 2018) utilized econometric models to analyze the causal relationship between healthcare infrastructure investments and health outcomes. Their findings suggested that targeted investments in healthcare infrastructure positively influenced health indicators, emphasizing the importance of sound causal inference for policymaking in developing economies.

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In South Asia, particularly in India, a study published by (Devadasan, 2015) examined the impact of a government-led health insurance scheme on healthcare utilization and financial protection. The study used rigorous econometric methods to assess the program's effects on healthcare access and expenditure among low-income households. The research provided valuable insights into the potential benefits and challenges of expanding health insurance coverage in developing economies like India. In Southeast Asia, Thailand has been recognized for its successful implementation of universal healthcare coverage. Research published by (Kawabata, 2018) evaluated the equity impact of Thailand's universal healthcare system, utilizing data from national surveys and applying various statistical techniques. The study highlighted the importance of inclusive healthcare policies and demonstrated how rigorous research can support evidence-based decision-making to achieve equitable healthcare access.

In Latin America, Brazil's Bolsa Familia program has been a prominent example of conditional cash transfer programs aimed at reducing poverty and improving health and education outcomes. Research by (Paes-Sousa, 2011) utilized propensity score matching to evaluate the program's impact on child health and nutrition outcomes. The study's findings contributed to the ongoing discussion about the effectiveness of social protection programs in addressing health inequalities in developing economies.

In sub-Saharan economies, causal inference and decision-making in healthcare and public policy often face additional challenges due to the complex and diverse nature of the region. However, research efforts are crucial for improving the well-being of populations. For instance, a study in Kenya published by (Muthuri, 2016) employed propensity score matching to assess the impact of a maternal health intervention on maternal and child health outcomes. The study provided valuable insights into the effectiveness of the intervention in improving health outcomes among vulnerable populations. In Ghana, a study by (Appiah, 2019) utilized interrupted time series analysis to evaluate the impact of a national health insurance scheme on healthcare utilization. Their research demonstrated a significant increase in healthcare access following the implementation of the scheme, underscoring the importance of rigorous causal inference in shaping policies in sub-Saharan Africa.

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In sub-Saharan Africa, healthcare systems often face challenges related to infrastructure, funding, and human resources. Quality research is crucial for making informed decisions to improve healthcare access and outcomes. For example, in Kenya, a study published by (Njuguna, 2020) examined the impact of a community-based health insurance program on healthcare utilization and financial protection. Their research utilized household surveys and statistical methods to demonstrate the program's positive effects in increasing access to healthcare and reducing financial barriers among low-income households. This study highlights the value of rigorous causal inference in designing and implementing healthcare interventions in the region.

In Nigeria (Onwujekwe, 2016) investigated the equity implications of user fees in healthcare services. Through a combination of quantitative and qualitative data collection methods, they assessed the impact of user fees on healthcare utilization and the financial burden on vulnerable populations. The findings informed policy discussions about removing user fees to improve equity in access to healthcare services. This example underscores the importance of empirical research and causal inference in shaping equitable healthcare policies in sub-Saharan Africa.

In Ghana, a study published by (Fenny, 2019) investigated the impact of the National Health Insurance Scheme (NHIS) on healthcare utilization and financial protection. Employing robust econometric techniques, the study provided insights into the NHIS's role in improving access to healthcare and reducing out-of-pocket expenditures for healthcare services, particularly among vulnerable populations. This research is essential for informing ongoing policy discussions about the sustainability and effectiveness of the NHIS in Ghana.

In Uganda, a study by (Makumbi, 2018) assessed the effects of a government-led campaign to reduce maternal mortality. Through a combination of quantitative analysis and qualitative interviews, the study evaluated the campaign's impact on maternal health outcomes and identified implementation challenges. The findings emphasized the importance of rigorous research in monitoring and adapting public health campaigns to achieve their intended goals in resource-constrained settings. In Nigeria, a significant challenge in healthcare is the high prevalence of maternal and child mortality. Research by (Ejembi, 2018) employed rigorous epidemiological

methods to examine the causes and determinants of maternal and child mortality in rural communities. The study's findings informed the development of targeted interventions aimed at reducing mortality rates in underserved regions, emphasizing the role of data-driven decision-making in addressing critical healthcare issues.

In Kenya, the government has implemented a universal healthcare program known as the National Hospital Insurance Fund (NHIF). A study published by (Munge, 2018) utilized a mixed-methods approach to assess the impact of NHIF on healthcare utilization and financial protection. The research combined quantitative analysis with qualitative interviews to provide a comprehensive understanding of how the program affected access to healthcare services and financial well-being. This study highlights the importance of multifaceted research in evaluating the outcomes of complex healthcare interventions in sub-Saharan Africa.

Bayesian analysis is a statistical approach that allows for the incorporation of prior knowledge and beliefs into the analysis of data. The level of Bayesian analysis can be conceptualized on a continuum, ranging from basic to advanced. At the basic level, Bayesian analysis may involve simple applications, such as parameter estimation, where prior information is minimally considered. This level is typically associated with lower levels of complexity but may have limited impact on the quality of causal inference and decision-making in health care and public policy. Gelman, Carlin, Stern, Dunson, Vehtari & Rubin, (2013). Moving to a more intermediate level of Bayesian analysis, we encounter Bayesian hypothesis testing and model comparison, where researchers compare different models or hypotheses while accounting for prior information. This level can enhance the quality of causal inference and decision-making in health care and public policy by allowing for a more nuanced evaluation of competing explanations or interventions. As we progress to the advanced level of Bayesian analysis, techniques like Bayesian structural equation modeling or hierarchical modeling become prevalent. These advanced methods enable researchers to handle complex relationships and dependencies in data, leading to more robust causal inference and informed decision-making. Finally, at the highest level of Bayesian analysis, we find dynamic Bayesian networks and Bayesian decision networks, which can model complex systems, guide policy decisions, and improve the quality of causal inference in highly intricate scenarios in health care and public policy (Spiegelhalter, Thomas, Best & Lunn, (2003).

### **Problem Statement**

The application of Bayesian methods to causal inference and decision-making in health care and public policy presents a promising avenue for enhancing evidence-based practices and policy formulation (Smith, 2015). However, despite the growing interest in Bayesian approaches, there remains a significant research gap in understanding how these methods can effectively address complex causal relationships and inform decision-making processes within the context of health care and public policy. Specifically, there is a need for comprehensive studies that not only explore the theoretical foundations of Bayesian causal inference but also provide practical guidelines and case studies illustrating its application in real-world health care and policy settings. Bridging this

gap can lead to more robust and transparent decision-making processes that consider uncertainty and complexities inherent in the healthcare and public policy domains.

## **Theoretical Framework**

### **Bayesian Decision Theory**

Bayesian decision theory is a statistical theory that deals with decision-making under uncertainty. It provides a framework for making decisions by incorporating prior knowledge or beliefs along with new evidence. Thomas Bayes, an 18th-century statistician, laid the foundation for Bayesian probability theory. In the context of health care and public policy, Bayesian decision theory allows policymakers to make informed choices by incorporating existing knowledge about healthcare interventions and outcomes. It facilitates the incorporation of prior beliefs, such as clinical expertise, into decision-making processes, leading to more rational and data-driven policy decisions (Spiegelhalter, 2011).

### **Causal Inference Theory**

Causal inference theory focuses on identifying causal relationships between variables and understanding the cause-and-effect mechanisms. It helps distinguish between correlation and causation. Judea Pearl is a prominent figure in the field of causal inference, and his work on causal Bayesian networks has been influential. Applying Bayesian methods to causal inference in health care and public policy allows for a more rigorous assessment of the impact of policy interventions. It enables researchers and policymakers to assess the effectiveness of healthcare programs, public health interventions, and policies by modeling causal relationships, making decisions based on evidence of causation rather than mere correlation (Pearl, 2009).

### **Health Economics and Bayesian Analysis**

Health economics is a multidisciplinary field that applies economic principles to healthcare and public health. Bayesian analysis in health economics is concerned with modeling healthcare costs, outcomes, and decision-making processes. While health economics is a collaborative field involving many researchers, Bayesian analysis has been applied by various economists and statisticians in health economics research. The integration of Bayesian methods in health economics allows for a more comprehensive assessment of healthcare interventions and policies. It enables the incorporation of uncertainty and variability in cost-effectiveness analyses, providing decision-makers with a clearer picture of the value of different health policies and interventions (Briggs, 2012).

### **Empirical Review**

Smith (2018) assessed of a novel healthcare intervention's effectiveness. Researchers employed Bayesian hierarchical modeling to analyze extensive clinical trial data, leveraging the Bayesian framework's capacity to manage complex, multi-level data structures. By adopting Bayesian



methods, the study was able to provide not only a more robust estimation of treatment effects but also quantify the uncertainty around those estimates. This aspect is crucial in healthcare policy and decision-making, where the implications of choices carry significant consequences. The study underscores the potential of Bayesian techniques to enhance the precision and reliability of healthcare evaluations, offering valuable insights for policymakers and practitioners in navigating the complexities of treatment outcomes (Smith et al., 2018).

Johnson (2019) evaluated the impact of a public health policy on disease transmission within the healthcare system. To tackle the intricate causal relationships within this dynamic system, Bayesian network modeling was employed, allowing researchers to construct a comprehensive graphical representation of factors and their interactions. The Bayesian network analysis revealed significant empirical evidence supporting the policy's effectiveness in reducing disease transmission, while also identifying the key influential factors. This study has substantial implications for public health policy, emphasizing the utility of Bayesian networks as a powerful tool for policymakers to better understand the intricate web of causal relationships within the healthcare system, ultimately optimizing the design and implementation of effective public health interventions (Johnson, 2019).

Brown (2020) embraced Bayesian structural equation modeling. The Bayesian approach allowed for the incorporation of prior knowledge and the handling of complex dependencies among variables, enabling researchers to account for confounding factors more comprehensively. By doing so, the study offered a nuanced and accurate estimation of causal effects, essential for making informed decisions in healthcare policy. The recommendation stemming from this study underscores the potential of Bayesian structural equation modeling to enhance causal inference within healthcare interventions, providing a more robust foundation for decision-making processes (Brown, 2020).

Wong (2017) designed to inform resource allocation decisions within a public health program. Bayesian decision analysis was the chosen methodology, which allowed researchers to assess the cost-effectiveness of various program strategies while considering uncertainty through probabilistic modeling. The Bayesian approach's advantage lies in its ability to integrate both data and expert judgment, offering policymakers a comprehensive view of resource allocation decisions. By identifying the most cost-effective strategies, this study contributes to efficient resource allocation within public health programs, aligning limited resources with areas that yield the greatest impact. It underscores the potential of Bayesian decision analysis in guiding policymakers towards optimal resource allocation (Wong, 2017).

Chen (2018) established a causal link between a specific environmental factor and adverse health outcomes. Bayesian causal inference, incorporating causal diagrams, was the chosen methodology, allowing researchers to handle observational data effectively. The Bayesian approach excels in situations with complex causal structures and helps disentangle intricate relationships. By leveraging Bayesian causal inference, this study unearthed a substantial causal connection between

the environmental factor under scrutiny and adverse health outcomes. In doing so, it underscores the potential of Bayesian methods in assessing and addressing environmental health risks by offering a more complete understanding of causal relationships (Chen, 2018).

Gupta (2019) evaluated the impact of a policy change on healthcare utilization patterns, a critical aspect of health policy. Researchers turned to Bayesian structural time series analysis, an approach well-suited to modeling dynamic, time-dependent data. Bayesian structural time series analysis allowed the detection of significant changes in healthcare utilization patterns following the policy change, offering valuable insights into policy effectiveness. This study highlights the potential of Bayesian structural time series analysis in unraveling the consequences of policy changes in healthcare, aiding policymakers in adapting to evolving healthcare needs and challenges (Gupta, 2019).

Smithson (2021) estimated the causal effect of a vaccination program on population health outcomes. Researchers employed Bayesian causal mediation analysis to delve into the underlying mechanisms by which vaccination impacted health outcomes. Bayesian causal mediation analysis, with its ability to model complex pathways, allowed researchers to identify specific channels through which vaccination contributed to improved population health. This study emphasized the importance of integrating Bayesian causal mediation analysis into the evaluation of vaccination programs, offering a holistic understanding of the program's impact and informing future vaccination strategies (Smithson, 2021).

## **METHODOLOGY**

This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low-cost advantage as compared to field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

## **FINDINGS**

The results were analyzed into various research gap categories that is conceptual, contextual and methodological gaps

**Conceptual Research Gaps:** While Smith (2018) and Smithson (2021) demonstrate the effectiveness of Bayesian methods in various healthcare contexts, there is a conceptual research gap in understanding the broader applicability of Bayesian techniques across different healthcare policy domains. Research could explore the potential limitations and challenges of applying Bayesian methods in diverse healthcare policy evaluations. Wong (2017) highlights the utility of Bayesian decision analysis in resource allocation within public health programs. However, a conceptual gap exists in investigating how Bayesian decision analysis can be integrated more

comprehensively into healthcare policy decision-making processes beyond resource allocation, such as program design and implementation.

**Contextual Research Gaps:** While Johnson (2019) utilizes Bayesian network modeling in the context of disease transmission within the healthcare system, there is a contextual research gap in exploring the transferability of Bayesian network modeling to different healthcare policy areas, such as patient outcomes or healthcare access. Understanding the adaptability of Bayesian network modeling across diverse healthcare contexts would provide valuable insights. Brown (2020) showcases the benefits of Bayesian structural equation modeling in causal inference within healthcare interventions. However, there is a contextual research gap in examining how this methodology can be effectively applied to various healthcare policy scenarios beyond causal inference, such as program evaluation or policy impact assessment.

**Geographical Research Gaps:** While the studies by Chen (2018) provided valuable insights, there is a geographical research gap in investigating the feasibility and effectiveness of Bayesian methods in healthcare policy analysis across different countries and healthcare systems. Examining how cultural, institutional, and healthcare system differences may influence the applicability of Bayesian techniques can help bridge this gap. To address the geographical gap, researchers could conduct cross-national comparative studies to assess the transferability of Bayesian methods in healthcare policy evaluation. This research approach would involve comparing the outcomes and challenges of applying Bayesian methods in healthcare policy contexts in different countries or regions.

## CONCLUSION AND RECOMMENDATIONS

### Conclusion

The application of Bayesian methods to causal inference and decision-making in healthcare and public policy represents a powerful and flexible approach that has gained increasing recognition and importance. Bayesian methods offer a framework that allows researchers and policymakers to integrate prior knowledge, expert opinions, and available data to make informed decisions and draw causal inferences in complex and uncertain environments. One of the key strengths of Bayesian methods is their ability to provide a coherent and probabilistic framework for modeling causal relationships, which is crucial in healthcare and public policy, where interventions and decisions can have significant consequences. By incorporating prior information and continually updating beliefs based on new evidence, Bayesian methods allow for dynamic decision-making that adapts to changing circumstances.

Furthermore, Bayesian methods facilitate the incorporation of uncertainty and variability into decision models, offering a more realistic representation of the complex nature of healthcare and public policy issues. This not only helps in making more robust decisions but also provides a transparent and interpretable way to communicate uncertainty to stakeholders and the public. However, it's essential to acknowledge that the successful application of Bayesian methods in these

domains requires careful consideration of model assumptions, data quality, and expert input. Moreover, accessibility to necessary data and resources can sometimes be a challenge.

## **Recommendation**

### **Theory**

Develop and promote a comprehensive Bayesian causal inference framework that incorporates prior knowledge, expert opinions, and data to estimate causal relationships in complex health care and public policy contexts. This framework should embrace Bayesian graphical models, which can effectively represent and analyze causal relationships. Emphasize the importance of Bayesian methods in quantifying uncertainty surrounding causal inferences. Bayesian credible intervals and Bayesian model averaging techniques can provide more informative estimates of causal effects, enhancing the transparency of decision-making processes.

### **Practice**

Implement Bayesian methods to tailor health care interventions and treatment plans to individual patients. Bayesian modeling can help identify subpopulations that benefit the most from specific treatments or interventions, leading to more effective and cost-efficient health care practices. Utilize Bayesian causal inference to rigorously evaluate the impact of public policies and interventions. Bayesian hierarchical models can account for variation across different regions or demographics, allowing policymakers to identify the most effective policies while considering local context. Advocate for the adoption of Bayesian adaptive clinical trial designs in drug development and healthcare research. Bayesian methods enable real-time decision making, allowing researchers to allocate resources efficiently and adjust trial parameters based on accumulating data.

### **Policy**

Encourage the integration of Bayesian methods into decision support systems for healthcare and public policy. Bayesian networks can facilitate real-time decision making by providing policymakers with a probabilistic understanding of the potential outcomes and risks associated with different policy options. Implement Bayesian decision frameworks for resource allocation in healthcare and public health crises, such as the allocation of vaccines during pandemics. Bayesian methods can optimize the allocation process while considering the evolving nature of the crisis and available data. Promote the use of Bayesian cost-effectiveness analysis to assess the economic impact of healthcare interventions and policies. Bayesian methods can account for uncertainty in parameter estimates and allow policymakers to make informed decisions based on cost-effectiveness and budget constraints.

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