The use of artificial intelligence for the development of health economic models

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Abstract

Objectives: Health economic models (HEMs) are used to inform decision-making in healthcare, including resource allocation and policy development. However, the construction and validation of these models can be time-consuming and resource-intensive. Artificial intelligence (AI) has the potential to revolutionize the development of health economic models. AI techniques, such as machine learning and natural language processing, can help to streamline the development of HEMs by automating data collection and analysis, by enabling faster and more accurate analysis of complex data sets, by identifying patterns and trends that may not be evident to human analysts, by streamlining the model development process and improving the accuracy and precision of models. This poster will illustrate some uses of AI for the development of HEMs.

One potential application of AI in HEMs is in the development of cost-effectiveness analyses. AI can be used to analyze large amounts of data on treatment outcomes and costs, and to identify the most cost-effective interventions. AI can also be used to forecast future trends in healthcare costs and utilization, enabling decision-makers to plan for resource allocation and policy development.

AI can also be used to optimize model structure and parameters. Machine learning algorithms can be used to identify the most important factors influencing the effectiveness and cost of a healthcare intervention, and to optimize the weighting of these factors in the final model. This can improve the accuracy and precision of the model and allow for a more detailed and nuanced understanding of the cost-effectiveness of the intervention.

Conclusion: The use of AI in the development of HEMs has the potential to significantly improve the accuracy and efficiency of decision-making in healthcare. Further research is needed to explore the full potential of AI in this area and to identify best practices for its use in health economic modeling.

Introduction

Healthcare systems worldwide are under increasing pressure to optimize resource allocation and policy development. Health economic models (HEMs) play a vital role in informing these decisions, but their construction and validation can be both time-consuming and resource-intensive (Drummond et al., 2015). The emergence of artificial intelligence (AI) offers an opportunity to revolutionize the development and implementation of HEMs, with a particular focus on enhancing the structure and programming of these models, ultimately leading to more efficient and accurate healthcare decision-making (Garrison et al., 2018).

This poster presentation explores the applications of AI techniques, such as machine learning and natural language processing, in refining the structure and programming of HEMs. A key aspect of this exploration is the use of AI in optimizing model structure and parameters. By employing machine learning algorithms, the most critical factors influencing the effectiveness and cost of a healthcare intervention can be identified (Marshall et al., 2020). This information can then be used to optimize the weighting of these factors in the final model, leading to improved accuracy, precision, and a more comprehensive understanding of the cost-effectiveness of the intervention.

While AI's potential in cost-effectiveness analyses is also significant, this presentation emphasizes its ability to streamline the model development process, automate data collection and analysis, and identify patterns and trends that may not be evident to human analysts (Karnon et al., 2013).

As the field of health economics continues to evolve, it is crucial to identify best practices for integrating AI into HEMs, with a particular focus on improving the structure and programming of these models, to maximize their benefits and transform the landscape of health economics.

Analyzing Big Data on Costs and Outcomes

Machine learning, a subset of AI, has proven to be a valuable tool for analyzing large and complex datasets on costs and treatment outcomes (Ravi et al., 2020). Traditional statistical methods often struggle to handle the volume and complexity of healthcare data, whereas machine learning algorithms can efficiently process and analyze large datasets to reveal patterns and relationships that may not be readily apparent to human analysts (Esteva et al., 2019).

By applying machine learning techniques to healthcare data, AI can identify factors that drive costs and influence treatment outcomes, leading to more accurate cost-effectiveness analyses. For example, AI algorithms can analyze Electronic Health Records (EHRs) to identify patient characteristics and treatment patterns that contribute to variations in costs and clinical outcomes (Bleich et al., 2021).

Predicting Trends in Healthcare Utilization and Integration into Health Economic Models

AI's ability to predict trends in healthcare utilization is particularly relevant when considering the impact of new health technologies. Deep learning, an advanced form of machine learning, can be employed to forecast healthcare utilization trends by training on historical data and identifying complex patterns that traditional methods might overlook (Yan et al., 2020).

By incorporating demographic, clinical, and socioeconomic data, as well as information on new health technologies, AI algorithms can generate more accurate predictions of healthcare utilization trends. These predictions can be integrated into health economic models to inform decision-makers about resource allocation and policy development, ensuring that healthcare systems are better prepared to meet the changing needs of their populations (Bishop et al., 2021).

The integration of AI-generated predictions into health economic models can provide a more comprehensive understanding of the potential impact of new health technologies on healthcare systems, taking into account factors such as cost-effectiveness, population health outcomes, and healthcare resource utilization (Karnon et al., 2013). This approach allows decision-makers to make more informed choices regarding the adoption and implementation of new technologies, ultimately leading to improved patient care and better use of limited resources.

AI for Optimization of HE Model Structure

The use of artificial intelligence (AI) for optimizing model structures has demonstrated significant advancements in various fields, including health economics. This section will delve into how AI techniques have been employed for optimizing model structures specifically in health economic models, with an emphasis on recent research.

Machine Learning

Machine learning techniques have been widely used for optimizing model structures in health economics, leading to improved performance and predictive capabilities. Techniques such as feature selection, dimensionality reduction, and hyperparameter tuning have been employed to enhance model structures by reducing complexity and improving generalization (Alaa & van der Schaar, 2019).

AI-driven optimization in health economic models can help identify the most critical factors influencing the effectiveness and cost of healthcare interventions and optimize the weighting of these factors in the final model (Jalal et al., 2017). This approach leads to more accurate and precise models, which in turn enable a more detailed understanding of the cost-effectiveness of healthcare interventions.

Reinforcement Learning

Reinforcement learning, a subset of machine learning, has been applied to model optimization in health economics, allowing for the discovery of optimal strategies and decision-making processes in complex environments (Sutton & Barto, 2018). This approach has been employed to optimize treatment strategies and healthcare interventions by learning the best actions to take based on the observed data, leading to more cost-effective and patient-centered approaches (Komorowski et al., 2018).

In a recent study, Zhang et al. (2020) utilized reinforcement learning to optimize treatment decisions in oncology, taking into account the trade-offs between treatment effectiveness, toxicity, and costs. This study demonstrates how AI-driven optimization can lead to more efficient resource allocation and better patient outcomes in the context of health economic models.

Deep Learning

Deep learning, an advanced form of machine learning, has shown promise in optimizing model structures for health economic models by capturing complex and nonlinear relationships in the data (Esteva et al., 2019). These techniques have been utilized in various health economic applications, such as predicting healthcare costs, forecasting disease progression, and simulating patient pathways (Bishop et al., 2021).

For example, Yang et al. (2021) proposed a deep learning-based model for predicting healthcare costs and utilization, integrating diverse data sources such as EHRs, claims data, and demographic information. This approach led to more accurate predictions, enabling better resource allocation and policy development in health economics.

Discussion

The use of AI techniques for optimizing health economic models offers numerous advantages but also comes with certain limitations and caveats. This section discusses the pros, cons, and caveats of employing AI in health economic model optimization in a scientific manner, including critical assessments from relevant literature.

AI techniques, such as machine learning and deep learning, can improve the accuracy and precision of health economic models by capturing complex and nonlinear relationships within the data (Alaa & van der Schaar, 2019; Bishop et al., 2021). AI-driven optimization also allows for automated feature selection and dimensionality reduction, which can streamline the model development process by identifying the most critical factors influencing the effectiveness and cost of healthcare interventions (Jalal et al., 2017). Furthermore, reinforcement learning techniques enable adaptive decision-making in health economic models by learning the best actions to take based on observed data, leading to more cost-effective and patient-centered approaches (Komorowski et al., 2018).

However, there are several limitations and caveats associated with AI-driven health economic model optimization. AI models can be prone to overfitting, where models perform well on the training data but fail to generalize to new, unseen data (Bishop, 2006). Strategies such as regularization and cross-validation can be employed to mitigate overfitting, but the risk remains a key concern. Another challenge is the interpretability and transparency of AI models, particularly deep learning models, which can be difficult to interpret due to their complex structures (Esteva et al., 2019). This lack of interpretability can hinder the adoption of AI-driven health economic models by decision-makers who require clear explanations of model outputs and their implications.

Data quality and availability are also critical factors in the performance of AI-driven models. AI techniques require large amounts of high-quality data for training and validation (Louppe, 2014). In health economics, data may be limited, incomplete, or subject to privacy restrictions, which can impact the performance of AI-driven models. Moreover, the use of AI in health economic models raises ethical concerns, such as potential biases in the data leading to unfair treatment recommendations or resource allocations (Obermeyer et al., 2019). Addressing these concerns requires careful consideration and transparency in model development and implementation.

In conclusion, AI techniques hold great promise for optimizing health economic models, improving their accuracy, precision, and adaptability. However, researchers and decision-makers must be aware of the limitations and caveats associated with AI-driven models, and address these challenges through careful model development, validation, and ethical considerations.

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