Quantitative approaches to sustainable health development: a comprehensive review

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Abstract: Recently, there has been a need for quantitative expression of diseases, health resources, medical challenges, and health systems through modeling, allocation, predictive analytics, and optimization. This review paper provides a comprehensive overview of mathematical applications in sustainable health development. Thus, the review examines the role of mathematical modeling, machine learning, biostatistics, and operations research in addressing complex health challenges. The Potential of mathematical applications to inform evidence-based decision-making, improve disease prevention and control, and enhance healthcare delivery was discussed. The paper also identifies gaps in current research and proposes future directions for mathematical applications in sustainable health development. The review has provided a valuable resource for researchers, policymakers, and healthcare professionals seeking to leverage mathematical applications for improved health outcomes.

Keywords: Modeling, epidemiology, Disease Modeling, Health Resource Allocation, Disease Prevention

1. Introduction

1.1 Background

Achieving sustainable health development has emerged as a top global concern. However, despite increasing awareness of its importance, a significant knowledge deficit persists regarding the most effective quantitative strategies to attain this objective. Quantitative strategies involve applying mathematical and statistical methods to examine and interpret data within specific fields like economics, biology, or social sciences. Mathematics serves as the foundation, providing essential tools and frameworks for quantitative analysis.

According to [11], mathematics is a discipline that begins with axioms and culminates in reality, exploring assumptions and their implications. It is a comprehensive field that encompasses the study of numerical patterns, geometric shapes, structural relationships, and their interconnectedness. Traditionally regarded as "The Queen of Science," mathematics has recently been integrated with medicine, yielding a synergistic relationship that fuels innovations in medical technology, treatment methods, and personalized care, ultimately advancing healthcare science and mathematical theories [16].

Sustainable health development refers to the process of creating and maintaining healthy populations and environments through equitable, efficient, and effective use of resources. It is born out of the United Nation's Sustainable Development Goals (SDGs), particularly Goal 3 (Good Health and Well-being).

1.2 Importance of Mathematics in Health Development

Mathematical applications have revolutionized the field of sustainable health development, enabling researchers and policymakers to tackle complex health challenges with precision and accuracy. Mathematical modeling, in particular, has been instrumental in understanding the dynamics of infectious diseases [5]. These applications have improved our understanding of disease dynamics, optimized resource allocation, and enhanced healthcare delivery (World Health Organization, 2019). Moreover, mathematical applications have informed evidence-based decision-making, disease prevention, and control strategies (Centers for Disease Control and Prevention, 2020). As the global health landscape continues to evolve, the role of mathematical applications in sustainable health development will become increasingly crucial. This review aims to provide a comprehensive overview of the current state of quantitative approaches in sustainable health development, highlighting recent advances, applications, and future directions.

1.3 Research Questions

i. What are the current quantitative approaches used in sustainable health development?

ii. What are the strengths and limitations of existing quantitative approaches in healthcare?

iii. How can quantitative approaches be integrated with healthcare policies and practices for sustainable development?

iv. What are the emerging trends and future directions in quantitative approaches for healthcare?

1.4 Aim and Objectives

This paper aims to review quantitative approaches to sustainable health development. The objectives for the review are to:

i. systematically review and synthesize existing literature on quantitative approaches in sustainable health development

ii. identify and categorize mathematical models, techniques, and tools used in healthcare

iii. evaluate the effectiveness and impact of quantitative approaches on healthcare outcomes

iv. highlight the challenges, emerging areas, and future research directions in quantitative approaches for healthcare

v. provide recommendations for healthcare stakeholders, policymakers, and researchers.

2. Mathematical modeling in healthcare

According to [36], mathematical modeling is the process of converting real-world problems into mathematical forms. The authors also noted that modeling entails formulating real-life situations into mathematical explanations, effectively translating complex problems into tractable and realistic representations. Mathematical modeling plays a vital role in healthcare, enabling researchers and practitioners to analyze complex biological systems, predict disease spread, and optimize treatment strategies [6]. By translating real-world health problems into mathematical representations, mathematical modeling facilitates evidence-based decision-making, improves patient outcomes, and enhances healthcare policy development [40].

2.1 Epidemiological Modeling

The integration of modeling into epidemiology, pioneered by scientists such as Anderson Gray McKendrick and Janet-Leigh Claypon in the early 20th century, has significantly enhanced outbreak control and public health decision-making [1, 48]. Epidemiological modeling leverages advanced mathematical and computational techniques to mimic the complex interactions driving disease transmission and spread within populations. By incorporating critical factors such as disease attributes, demographic variability, and intervention efficacy, these models enable researchers to better comprehend, forecast, and mitigate the impact of infectious diseases [14]. As stated by [27], epidemiological models constitute simplified mathematical frameworks that integrate disease transmission dynamics and population attributes, providing valuable insights into the progression of infectious diseases and guiding optimal control measures.

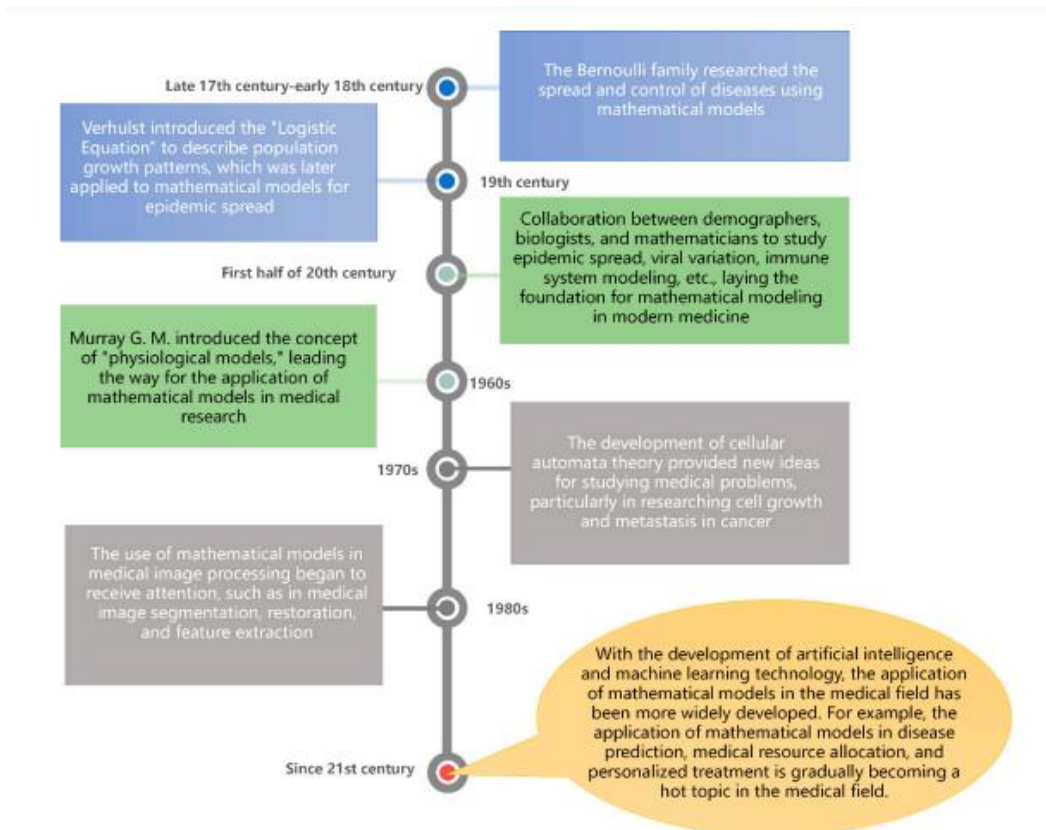

Fig. 1: Development of Mathematical Models Applied in Healthcare (Source: [24])

2.2 Mathematical Models in Epidemiology

The goal of epidemiological modeling is to gain insights into the dynamics of disease transmission and, where feasible, implement strategies to curb its propagation. This pursuit naturally leads to several fundamental questions:

• How quickly the disease spreads and how many people are susceptible to infection (He *et al.*, 2021).

• How much of the total population is infected or will be infected? [32].

• What are the control measures? [28].

• What are the effects of Migration/ Environment/Ecology, etc.?

• What is the chance of persistence of the disease? [13]

2.3 Classification of Models

There are multiple classifications of models:

a) Classification according to their objectives: Statistical, Mathematical, and Economic based

b) Classification according to the used inputs and structure: Compartmental, Compartmental with age, Agent-based, Network, Time series, Spatial, and Hybrid.

2.3.1 Statistical Model

It leverages data-driven insights to discern trends and patterns, facilitating nowcasting and forecasting of epidemiological dynamics. Additionally, this methodology assesses the efficacy and effectiveness of existing interventions, informing evidence-based decision-making [44]

2.3.2 Mathematical Model

It uses mathematical language to describe the complex interplay of biological and behavioral factors driving disease transmission. Upon validation, these models serve as robust tools for scenario analysis and predictive insights [20].

2.3.3 Compartmental (deterministic) Model

A compartmental model is one in which the individuals in a population are classified into compartments depending on their status about the infection under study. The relationship between these compartments is given by a system of differential equations [10]. Common departmental (deterministic) models include:

i. **SIR Model** (**S**usceptible, **I**nfected, **R**ecovered or **R**emoved):

S(t) - The susceptible population, i.e., the class of the population that tends be infected.

I(t) - The infective population, i.e., the class of the population that has contracted the disease and can transmit it to the susceptible population.

R(t) - The recovered or removed population, i.e., the class of the population that has recovered from the disease and that is considered immune.

With this, the total population N can be expressed as

$$N = S(t) + I(t) + R(t) \qquad (1)$$

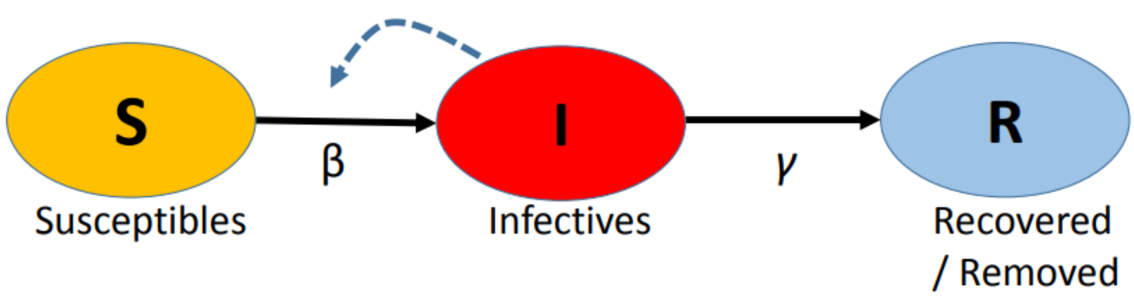

Fig. 2: SIR Model

The system of differential equations associated with Figure 2 is given below:

$$\frac{dS}{dt} = -\beta SI$$
$$\frac{dI}{dt} = \beta SI - \gamma I \qquad (2)$$
$$\frac{dR}{dt} = \gamma I$$

With the initial conditions $S(0) > 0, I(0) > 0$ and $R(0) = 0.$ (3)

β is the rate at which susceptible individuals get infected while γ is the rate at which infected individuals recover from infection. The disease will be in equilibrium state (S*, I*, R*) at a point where $\boldsymbol{dS/dt} = \boldsymbol{dI/dt} = \boldsymbol{dR/dt} = 0$

ii. SIRS model: (**S**usceptible, **I**nfected, **R**ecovered, **S**usceptible)

It is an extension of the SIR model, incorporating an additional compartment to account for waning immunity [50]

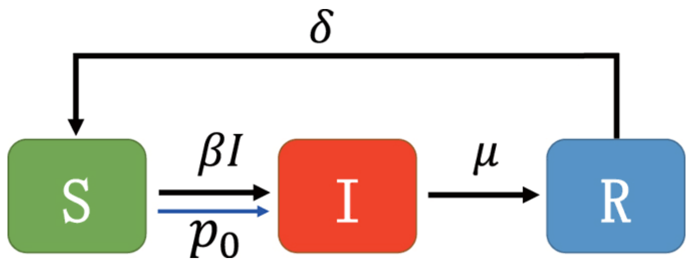

Fig. 3: SIRS Model

iii. SEIR Model (**S**usceptible, **E**xposed, **I**nfected, **R**ecovered or **R**emoved):

It involves exposed individuals who contracted the infection but still non-infectious (latent period of the disease) [25]

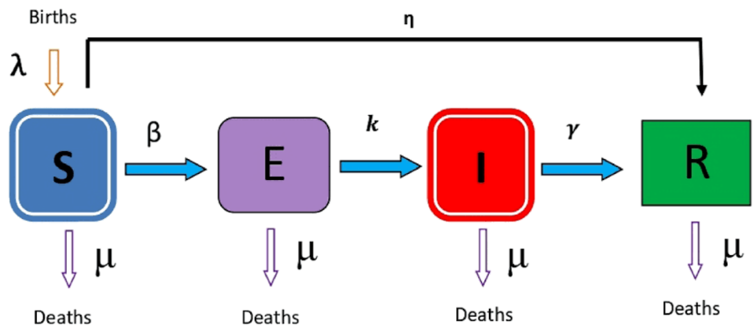

Fig. 4: SEIR Model

iv. SAPHIRE Model:

It includes seven compartments: Susceptible (**S**), Asymptomatic (**A**), Pre-symptomatic (**P**), Hospitalized (**H**), Infected (**I**), Recovered (**R**), and Exposed (**E**).

The SAPHIRE Model has applications in COVID-19 modeling, Influenza pandemic planning, and Hospital capacity planning.

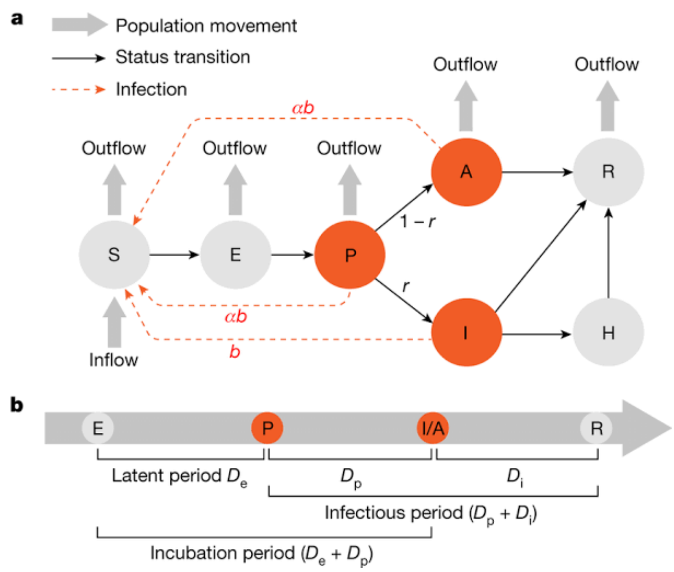

Fig. 5: Illustration of the SAPHIRE Model

2.4 Basic Reproductive Ratio (R_0 – pronounced as "R naught")

The Basic Reproductive Ratio (R0) is a crucial epidemiological metric that measures the infectiousness of a disease, representing the average number of people an infected individual will infect, assuming a fully susceptible population [51]. It is not a biological constant for a pathogen as it is also affected by other factors such as environmental conditions and the behavior of the infected population [52].

An R0 value of 1 marks a critical threshold, separating epidemic from non-epidemic scenarios. At this value, each existing case generates exactly one new case, resulting in a stable, endemic situation without exponential growth or outbreak.

If $R_0 > 1$, each existing infection causes more than one new infection. The disease will be transmitted between people, and there may be an outbreak or epidemic.

If $R_0 < 1$, each existing infection causes less than one new infection. In this case, the disease will decline and eventually die out.

2.4.1 Incidence of R_0 for some selected diseases

Table 1: Value of R_0 for some diseases

Disease	Value of R_0	Source
Swine Flu (1918)	$1.4 < R_0 < 2.8$	[8]
H1N1 Virus (2009)	$1.4 < R_0 < 1.6$	[53]
COVID-19	5.7	[54]

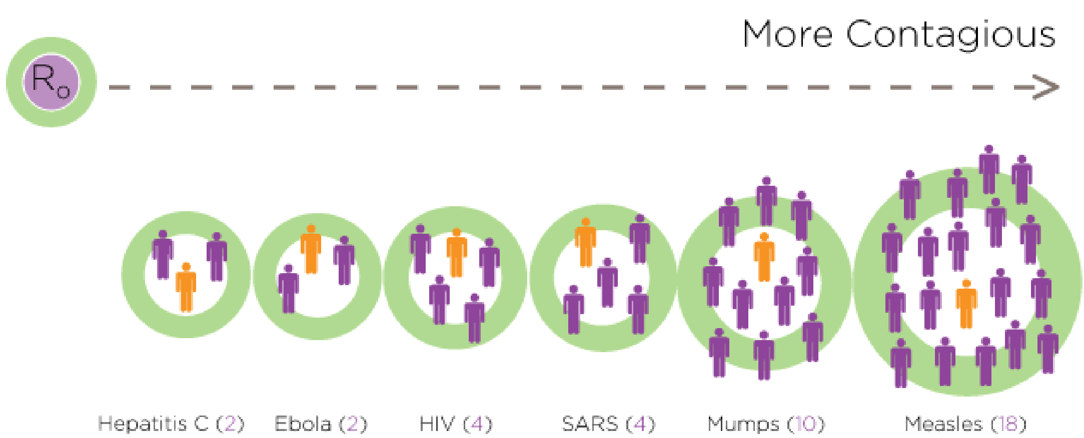

Fig. 6: Illustration of some commonly known diseases and their estimated R_0 value

(Source: https://www.healthline.com/health/r-naught-reproduction-number#prevention)

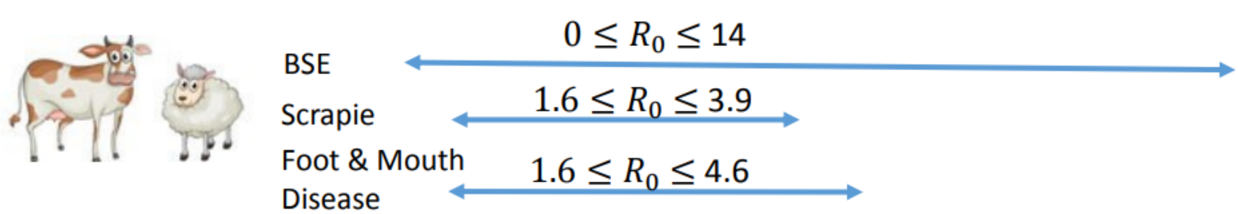

Fig. 7: R_0 value for some animal diseases

2.5 Role of Biostatistics in Analyzing Public Health

The field of biostatistics involves the application of statistical techniques to various biological disciplines, including public health [46]. The rise of emerging diseases and infection rates underscores the significance of biostatistical analysis in understanding disease patterns. Effective biostatistical practice requires technical proficiency in mathematical calculations and statistical tools [26]. Educational initiatives and training programs play a crucial role in bridging knowledge gaps. Biostatistics is instrumental in determining health outcomes and informing public health policy decisions, particularly during epidemics and pandemics [23].

Biostatistics aids in identifying public health issues, detecting data inaccuracies, correcting missing responses, and evaluating medical treatment effectiveness to inform policy changes. Additionally, probability helps estimate health outcomes in medicated and non-medicated populations by measuring event likelihood [9].

3. Data analytics and machine learning in healthcare

Data analytics has revolutionized healthcare by tapping into the wealth of data generated within the sector, unlocking new insights and opportunities [34]. Building on this, research highlights the potential of advanced analytics techniques, such as predictive modeling and machine learning, to extract valuable insights from complex datasets [33]. This informs decision-making and drives proactive care models.

3.1 Evolution of Data Analytics in Healthcare

The development of data analytics in healthcare has been shaped by technological advancements, regulatory changes, and the increasing recognition of data-driven decision-making’s importance [41]. The transition from paper-based to digital data storage systems, facilitated by Electronic Health Records (EHRs), laid the groundwork for contemporary data analytics [17]. Early efforts focused on descriptive analytics, while subsequent advancements in computational power and analytics and AI applications [2, 18].

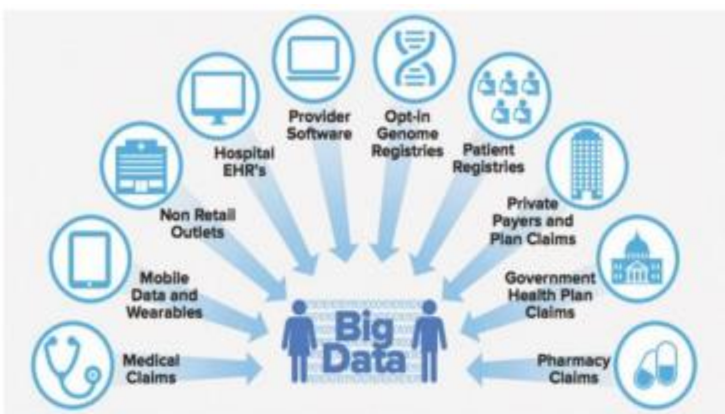

Fig. 8: Big Data Analytic in Healthcare (Source: [45])

3.2 Types of Healthcare Data

[12, 30, 31] noted that healthcare data encompasses a series of information generated and retrieved within the healthcare ecosystem. They include:

3.2.1 Clinical Data

Clinical data is the data which is collected during the ongoing treatment of the patient including the Electronic Health Record (EHR) data which is comprised of laboratory tests, radiology images, allergies and so on.

3.2.2 Administrative Data

Administrative data constitutes billing and claims data, insurance information, demographic data, and healthcare utilization statistics. It is used for administrative purposes such as billing, reimbursement, and resource allocation within healthcare organizations.

3.2.3 Patient-Generated Data

With the rise of wearable devices, mobile health apps, and remote monitoring technologies, patients are increasingly generating health-related data outside of traditional clinical settings. Patient-generated data includes information such as activity levels, vital signs, sleep patterns, and medication adherence, captured through wearable sensors, smartphone apps, and patient portals.

3.2.4 Sensor Data

Data produced by sensors including time series signals which is an ordered sequence of pairs is referred to as Sensor Data. These data are processed by computing devices and can be simple numerical or categorical values or can be more complex data. [55] have applied sensor data. They proposed machine learning algorithms to detect Parkinson's disease (PD) by using data streams collected from wearable sensors.

3.2.5 Genomic data

Genomic data is the collection of gene expression, copy number variation, sequence number, and DNA data and is used in bioinformatics. The work on genomic data is applied by [29]. They proposed machine learning algorithms for improving hazard characterization in microbial risk assessment.

Each type of healthcare data offers unique insights into patient health, disease management, and healthcare delivery, and when integrated and analyzed collectively, they provide a comprehensive view of a patient's health status and care journey [30].

3.3 How Machine Learning (ML) Revolutionizes Healthcare

Machine learning (ML) is a multidisciplinary field, drawing from mathematics, statistics, knowledge analytics, and data processing. This complexity makes defining ML challenging. As a distinct type of artificial intelligence, ML utilizes data for self-directed training, leveraging various branches and sub-branches to identify patterns [21, 49].

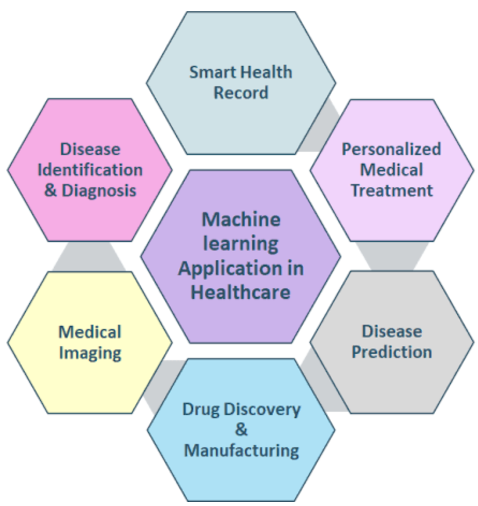

Fig. 9: Machine Learning Application in Healthcare

Healthcare utilizes various algorithms, including deep learning, regression, ensemble methods, decision trees, and artificial neural networks. Specifically, convolutional neural networks (CNN), artificial neural networks (ANN), random forests, support vector machines (SVM), and logistic regression are widely applied [35, 37, 43]. A comprehensive summary of Machine Learning Techniques and their applications is presented in the table below, as outlined by [47]

Table 2: ML techniques and their applications in the healthcare sector

S/N	Machine Learning Techniques	Applications in Healthcare	References
1	Convolutional neural networks (CNN)	Medical image understanding	[35]
2	Artificial neural network (ANN)	Cancer prediction, clinical diagnosis, length of stay prediction, speech recognition	[37]
3	Support vector machine (SVM)	Medication adherence predictor in heart failure	[43]
4	Logistic regression	Predict the likelihood of a patient’s readmission	[22]
5	Random forest	Medical data classification	[3]
6	Deep neural network (DNN)	Predicting depression risk	[56]
7	Decision tree	Medical insurance fraud	[42]
8	K-nearest neighbor (KNN)	Diagnosing heart disease	[15]
9	Recurrent neural network (RNN)	Medical data analysis and classifications	[4]
10	Naive Bayes	Sentimental analysis for positive and negative reviews of the patients	[7]

4. Mathematical modeling for health decision-making

Authors in [38] conducted an extensive examination of the role of epidemiological modeling in public health decision-making in sub-Saharan Africa, focusing on South Africa, Kenya, and Ghana. Their findings provide a foundational framework for developing regional capacity in epidemiological modeling. Notably, they emphasize that investing in human capital through training, mentoring, and talent development is crucial, rather than significant capital expenditures on laboratories or equipment.

4.1 Epidemiological modeling to inform public health decision making

4.1.1 A Case Study of Kenya

At the onset of the COVID-19 pandemic, Kenya's Ministry of Health established a committee of experts in mathematical modeling, epidemiology, laboratory science, and policy to facilitate evidence-informed decision-making. As the epidemic progressed, policymakers sought guidance on intervention effectiveness and relied on modeling to:

- Forecast virus transmission
- Evaluate community-based interventions
- Assess vaccine impact

These efforts informed Kenya's response, incorporating WHO-recommended measures and vaccination rollout [57].

4.1.2 A Case Study of Ghana

As observed by [38], epidemiological modeling in Ghana, before COVID-19, was primarily applied to malaria and HIV research. Studies employed diverse models to investigate disease transmission and intervention effectiveness. Malaria research focused on population dynamics and intervention impacts. In response to COVID-19, Ghanaian scholars from biostatistics, statistics, and mathematics departments utilized mathematical models to analyze transmission dynamics and epidemic trajectories.

4.1.3 A Case Study of South Africa

According to [38], South Africa is renowned for its exceptional scientific research capacity in Sub-Saharan Africa, hosting world-class institutions such as the South African COVID-19 Modelling Consortium (SACMC). This capacity enables the country to leverage mathematical disease modeling, exceeding that of its regional counterparts. The South African case study serves as:

- A benchmark for aspiring SSA countries
- A resource for collaborative capacity strengthening
- An illustration of persistent challenges despite advanced capacity

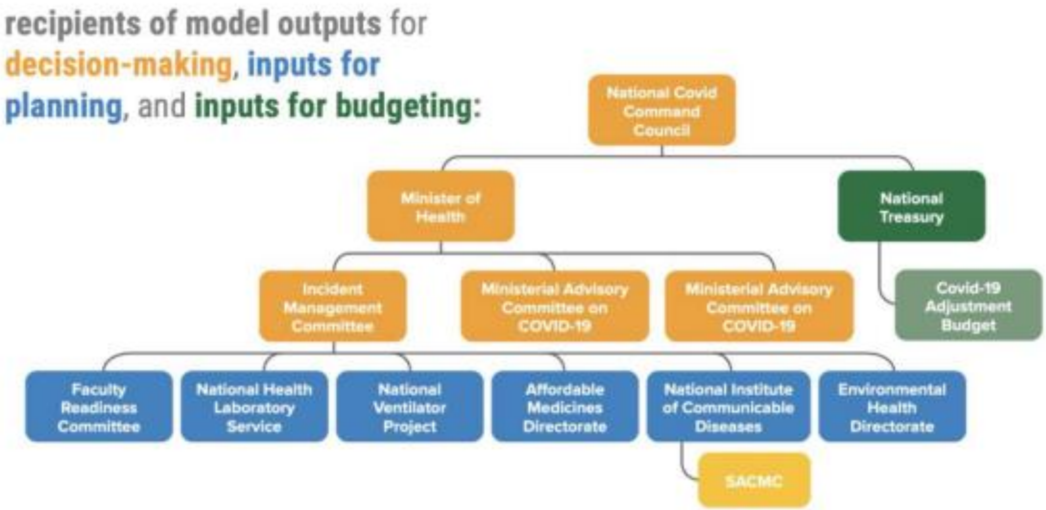

Fig. 10: Hierarchy of Epidemiological Model for Decision Making (Source: [38])

4.2 Challenges and Future Directions

4.2.1 Challenges

It is essential to acknowledge that mathematical models in healthcare are susceptible to biases and errors due to the inherently limited nature of medical and health-related data. Furthermore, despite efforts to incorporate diverse variables, crucial factors may remain unaccounted for, compromising model accuracy [24].

Future advancements in machine-learning-based medical models must address:

- Enhanced accuracy and efficiency
- Robust data privacy and security measures
- Model interpretability and transparency
- Synergistic integration with medical expertise

The complexity of medical data necessitates substantial computational resources. Data sharing and processing face restrictions due to privacy concerns.

4.2.2 Future Directions

The application of mathematical models in healthcare will continue to expand, driven by multidisciplinary collaboration. Key technologies enabling this growth include:

- High-performance computing: Enhancing data analysis, disease mechanism understanding, and treatment development.
- Deep learning: Improving disease diagnosis, genomics, drug development, and personalized treatment.
- Virtual reality: Enhancing medical simulation, surgical training, disease progression prediction, and psychological disorder treatment.

- Gene editing technology: Enabling precise treatment of hereditary diseases and individualized treatment plans.
- Blockchain technology: Securing medical data sharing, analyzing disease trends, and improving prevention and control strategies.

Other areas of future consideration include:

- Personalized Medicine
- Predictive Analytics
- Precision Health
- Digital Health
- Synthetic Biology
- Artificial Intelligence (AI) Integration
- Multi-scale Modeling

5. Conclusion and recommendations

5.1 Conclusion

In conclusion, this comprehensive review highlights the pivotal role of quantitative approaches in advancing sustainable health development. The integration of mathematical models, data analytics and machine learning has revolutionized our understanding of complex health systems, disease dynamics, and intervention strategies. The evidence presented demonstrates the potential of quantitative approaches to:

- Inform health policy and decision-making
- Optimize disease control
- Enhance personalized medicine and precision health
- Foster collaborative research and interdisciplinary approaches

Despite significant progress, challenges persist, which include:

- Data quality and standardization
- Model validation and interpretability
- Integration with electronic health records

5.2 Recommendations for future research

The following are recommended for future research:

- Develop and validate mathematical models for emerging health threats
- Investigate the application of machine learning in healthcare
- Explore the potential of synthetic biology in disease prevention
- Develop user-friendly software for mathematical modeling in health

5.3 Implication for Policy and Practice

To bridge the gap between research and real-world application, and ultimately contribute to sustainable health development, the following implications for policy and practice are presented:

- Integrate mathematical modeling into public health decision-making
- Inform health policy with data-driven insights
- Foster interdisciplinary collaboration between mathematicians, clinicians, and policymakers
- Invest in health information technology infrastructure

Reference

1. A. E. Abdelsalam, E. M. Mahfouz, Preprint (2024).

2. Z. Ahmed, K. Mohamed, S. Zeeshan, X. Dong, Database 2020, baaa010.

3. M. Z. Alam, M. S. Rahman, M. S. Rahman, Informatics in Medicine Unlocked **15** (2020) 100180.

4. H. Al-Askar, N. Radi, Á. MacDermott, Applied Computing in Medicine and Health 147-165 (2016).

5. R. M. Anderson, H. Heesterbeek, D. Klinkenberg, T. D. Hollingsworth, Nature Reviews Physics **2**(1), 1 – 13 (2020).

6. D. Bingham, S. Gillespie, L. Kanya, Wiley (2012).

7. K. Chakrapani, M. Kempanna, S. M. Iqubal, K. Thyagarajan, M. Ramachandran, V. Bhaskar, A. Kumar, (link unavailable) (2021). https://doi.org/10.21203/rs.3.rs-620229/v1.

8. B. J. Coburn, B. G. Wagner, S. Blower, BMC Med **7**(30) (2009).

9. S. Collinson, K. Khan, J. M. Heffernan, PloS one **10**(11), e0141423 (2015).

10. A. Dhar, Indian Academy of Sciences Conference Series; **3**(1) (2020).

11. K. Y. Dharmendra, International Research Journal of Mathematics, Engineering and IT **4**(1), 34 – 42 (2017).

12. A. Dhillon, A. Singh, Journal of Biology and Today's World (2018).

13. P. L. B. Diana, G. Hayriye, K. Ralph, P. Y. María, Applied Mathematical Modeling **111**, 739-752 (2022).

14. R. Djidjou-Demasse, C. Selinger, M. T. Sofonea, Revue francophone des laboratoires : RFL 2020(526), 63–69 (2020).

15. A. Enriko, S. Yusuf, Front Public Health; **9**: 645405 (2021).

16. M. I. Razzak, M. Imran, G. Xu, Neural Computing and Applications **32**(9), 4417-4451 (2020).

17. A. Rehman, S. Naz, I. Razzak, Multimedia Systems **28**(4), 1339-1371 (2022).

18. D. R. Sarvamangala, R. V. Kulkarni, Evol. Intel. **15**, 1–22 (2022).

19. D. Sefa, M. Burcin, S. Yasin, Procedia – Social and Behavioural Sciences **46**, 3465 – 3470 (2012).

20. C.F. Javier, F.M. Ursula, & L.L. Matilde, Mathematics, **10**, 3347, (2022).

21. S. Silal, C. Bardsley, R. Menon, L. Abullahi, L. White, Foreign, Commonwealth and Development Office, London (2022).

22. S. P. Silal, J. R. C. Pulliam, L. Jamieson, B. E. Nichols, H. Moultrie, M. Meyer-Rath, South African Health Review, Health Systems Trust, Durban (2021).

23. B. Smith, R. Zielinski, J. Ehrenfeld, Journal of Healthcare Engineering **6**(2), 247 – 266 (2015).

24. M. Smuck, C. A. Odonkor, J. K. Wilt, N. Schmidt, M. A. Swiernik, NPJ digital medicine **4**(1), 1-8 (2021).

25. F. SoleimanianGharehchopogh, P. Mohammadi, P. Hakimi, International Journal of Computer Applications **52**(6), 21–26 (2012).

26. Y. J. Son, H. G. Kim, E. H. Kim, S. Choi, S. K. Lee, Healthcare Informatics Research **16**(4), 253–259 (2010).

27. K. Subhash, Y. Yusuf, Front Public Health; **9**: 645405 (2021).

28. S. Moore, E.M. Hill, M.J. Tildesley, L. Dyson, M.J. Keeling, Lancet Infect Dis, Vaccination and non-pharmaceutical interventions for COVID-19: A Mathematical Modelling Study, 18, doi: 10.1016/S1473-3099(21)00143-2 (2021)

29. P. M. Njage, P. Leekitcharoenphon, T. Hald, Int. J. Food Microbiol. **292**, 72-82 (2019).

30. P. Nong, J. Adler-Milstein, S. Kardia, J. Platt, J. Am. Med. Inform. Assoc. ocae009 (2024).

31. C. S. Nwaimo, A. E. Adegbola, M. D. Adegbola, GSC Biol. Pharm. Sci. **27**(3), 25–35 (2024).

32. J. K. Peter, B. K. Paula, H. R. Nancy, Immunoepidemiology **28**, 227–243 (2019).

33. M. I. Razzak, M. Imran, G. Xu, Neural Comput. Appl. **32**(9), 4417-4451 (2020).

34. A. Rehman, S. Naz, I. Razzak, Multimed. Syst. **28**(4), 1339-1371 (2022).

35. D. R. Sarvamangala, R. V. Kulkarni, Evol. Intel. **15**, 1–22 (2022).

36. D. Sefa, M. Burcin, S. Yasin, Procedia Soc. Behav. Sci. **46**, 3465 – 3470 (2012).

37. N. Shahid, T. Rippon, W. Berta, PLoS ONE **14**(2): e0212356 (2019).

38. S. Silal, C. Bardsley, R. Menon, L. Abullahi, L. White, Foreign, Commonwealth and Development Office, London (2022).

39. S. P. Silal, J. R. C. Pulliam, L. Jamieson, B. E. Nichols, H. Moultrie, M. Meyer-Rath, South African Health Review, Health Systems Trust, Durban (2021).

40. B. Smith, R. Zielinski, J. Ehrenfeld, J. Healthc. Eng. **6**(2), 247 – 266 (2015).

41. M. Smuck, C. A. Odonkor, J. K. Wilt, N. Schmidt, M. A. Swiernik, NPJ Digit. Med. **4**(1), 1-8 (2021).

42. F. SoleimanianGharehchopogh, P. Mohammadi, P. Hakimi, Int. J. Comput. Appl. **52**(6), 21–26 (2012).

43. Y. J. Son, H. G. Kim, E. H. Kim, S. Choi, S. K. Lee, Healthc. Inform. Res. **16**(4), 253–259 (2010).

44. K. Y. Subhash, A. Yusuf, Front. Public Health **9**: 645405 (2021).

45. S. Z. Thalhah, M. Tohir, P. T. Nguyen, K. Shankar, R. Rahim, Int. J. Recent Technol. Eng. **8**, 4153 – 4156 (2019).

46. E. Velasco, Life Sci. Soc. Policy **14**(1), 1 - 6 (2018).

47. V. K. Verma, S. Verma, Mater. Today Proc. (2021).

48. P. Wang, L. Ja, M. Zhu, L. Wang, S. Chen, Int. J. Infect. Dis. **95**, 391–398 (2020).

49. X. D. Zhang, Springer (2020).

50. Q. Pan, J. Huang, H. Wang, J. Math. Biol. **85**, 23 (2022).

51. S. Dharmaratne, S. Sudaraka, I. Abeyahunawardena, K. Mnchanayake, M. Kothalawala, W. Gunathunga, Virol. J. **17**(144) (2020).

52. P. L. Delamater, E. J. Street, T. F. Leslie, Y. T. Yang, K. H. Jacobsen, Emerg. Infect. Dis. **25**(1), 1-4 (2019).

53. C. Fraser, et al., Science **324**, 1557-1561 (2009).

54. S. Sanche, Y. T. Lin, C. Su, E. Romero-Severson, N. Hengartner, R. Ke, High Contagiousness and Rapid Spread of Severe Acute Respiratory Syndrome Coronavirus 2. Emerg Infect Dis., **26**, 1470-1477 (2020)

55. L. Lonini, A. Dai, N. Shawen, T. Simuni, C. Poon, L. Shimanovich, M. Daeschler, R. Ghaffari, J.A. Rogers, A. Jayaraman, npj Digit Med, Wearable sensors for Parkinson's disease: which data are worth collecting for training symptom detection models, **1**, 64 (2018)

56. J.W. Baek, K. Chung, IEEE Access, Context Deep Neural Network Model for Predicting Depression Risk Using Multiple Regression, **8**, 18171-18181 (2020)

57. E.N. Wangari, P. Gichuki, A.A. Abuor, J. Wambui, S.O. Okeyo, H.T.N. Oyatsi, S. Odikara, B.W. Kulohoma, AAS Open Res, Kenya's response to the COVID-19 pandemic: a balance between minimizing morbidity and adverse economic impact, **4**(3) (2021)