



Cross-disciplinary mathematical modelling to benefit healthcare – could clinical pharmacology play an enabling role?

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Abstract

Clinical pharmacology is often the nexus in any cross-disciplinary team that is seeking solutions for human healthcare issues. The use and application of real-world data and artificial intelligence to better understand our ecosystem has influenced our view at the world and how we do things. This has resulted in remarkable advancements in the healthcare space and development of personalized medicines with great attributes from the application of models and simulations, contributing to a more efficient healthcare development process. A cross-disciplinary symposium was held in December 2023, whereby experts from different scientific disciplines engaged in a high-level discussion on the opportunities and challenges of mathematical models in different fields, possible future developments and decision making. A strong interlink amongst the disciplines represented was apparent, with clinical pharmacology identified as the one which integrates various scientific disciplines. Deliberate and strategic cross-disciplinary dialogues are required to break out of the silos and implement integration for efficiency and cost-effectiveness of novel interventions.

KEYWORDS

Africa, clinical pharmacology, cross-disciplinary, mathematical modelling, simulations

1 | BACKGROUND

Clinical pharmacology is often the nexus in any cross-disciplinary team that is seeking solutions for human healthcare issues. In this age of highly advanced technology, the use and application of real-world data and artificial intelligence to better understand our ecosystem has influenced how we look at the world and challenged how we do things. The healthcare space and the development of personalized

medicines have advanced remarkably, with good strides made through the application of models and simulations, contributing to a more efficient healthcare development process. For example, the science of pharmacometrics modelling has evolved from the introduction of the term “pharmacokinetics” in the 1950s through a paradigm shift in academic research by focusing on population variability (1980s) to the professional support of medicines development and regulatory approval (1990s). Nowadays, the scope of pharmacometrics modelling has broadened to translational medicine, use of genetic algorithms, machine learning and artificial intelligence.¹ Global health disease

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models evaluate disease progression, effects of interventions, epidemiology and health technology assessments, including health economic considerations. Climate change is associated with changes in disease patterns and in the use of medicines. Cross-disciplinary mathematical modelling of observation-based earth systems, epidemiology, agriculture and health economics can explore global health impacts and assist with decision making.

Given the interaction of interrelated systems, modelling and simulations from related areas such as climate change, agricultural science, genomics and epidemiology make it increasingly possible to predict and plan responses to emerging threats. Advances in physics and computational technology enable increasingly complex scenarios to be explored mathematically. However, drawing these aspects together to enable a “One Health” agenda requires deliberate and strategic cross-disciplinary dialogue.

In December 2023, Stellenbosch University, Fundisa African Academy of Medicines Development and Pharmacometrics Africa convened a virtual cross-disciplinary symposium to discuss concepts of mathematical modelling applied in various interrelated scientific fields, including the science of pharmacometrics. The meeting attracted a diverse global audience of 217 participants, with the majority from Africa (77.8%) followed by Europe (11.3%), Asia (5.9%), North America (3.9%) and Australia (1%).

Experts from different fields were invited to share their insights for a deeper understanding of the application, experiences, challenges and foresight of mathematical modelling in their fields. The goal was to provide an opportunity to highlight the current interlinks amongst the disciplines and possible avenues/collaborations for future research and applications.

The symposium was structured around the following major themes which served as guidance to steer the discussion amongst the panellists.

2 | OPPORTUNITIES AND CHALLENGES

The discussions on this theme aimed to identify and address challenges within each discipline, while also exploring potential opportunities for interdisciplinary collaborations by considering the following points:

- Current limitations in mathematical modelling techniques
- Overcoming the limitations of computation and data availability
- Identify any new advancements on the horizon
- Older technologies that are resurging or warrant another look
- Implications of the artificial intelligence (AI) revolution
- Communication with decision makers regarding use of and results from models and simulations

3 | FUTURE DEVELOPMENTS AND DECISION MAKING

Speakers and panellists discussed the current state of affairs providing a high-level perspective on potential impacts, current limitations and

TABLE 1 Speakers and topics of the Cross-Disciplinary Mathematical Modelling & Simulation Symposium 2023.

Speaker	Talk title
Prof. Sir Francesco Petruccione: Physicist, author & lecturer, Stellenbosch University and National Institute for Theoretical and Computational Sciences (NITheCS)	Keynote: Opportunities and challenges
Steve Kern: Executive Director, Global Health Labs	Opportunities and challenges to link individual with population models for predictive impact
Georg Feulner: Senior Scientist, Potsdam Institute for Climate Impact Research (PIK)	The challenges of modelling the coupled Earth system
Johanna Lister: Global Health Economics Lead, Takeda Pharmaceuticals	Health economic modelling for assessing the value of medicines
Prof. Patrick Noack: Scientific Director of Competence Center for Digital Agriculture, University of Applied Sciences, Weihenstephan-Triesdorf	Development of an automated solution for the drone-assisted assessment of field trials
Miriam Njoki Karinja: Clinical Epidemiologist/Senior Program Officer, Science for Africa (SFA) Foundation	Use of mathematical modelling to inform public health interventions
Catriona Waitt: Professor of Clinical Pharmacology and Global Health, University of Liverpool/Infectious Diseases Institute, Makerere University	Panel Discussion Chairperson

challenges with respect to the integral role of mathematical models and simulations in shaping decisions across multiple sectors such as health-care, including drug development, agriculture, climate change and public policy. The panel explored how the utility and impact of tools could vary significantly from one field to another, fostering a rich interdisciplinary dialogue. The list of speakers and topics is shown in Table 1.

3.1 | Quantum computing: Professor Sir Francesco Petruccione

The advancement of technology has seen the evolution of quantum mechanics to the birth of quantum computing. Though it can be expected that advancements in technology should bring improvements across the spectrum, this is not always the case. The era of quantum computing promises ultra-fast data processing, raising hope for many scientific disciplines for more efficient modelling tools, in terms of cost, time and resources required. This is currently not the case. Though quantum information science promises collection by precision measurements (for example, quantum metrology), efficient safe data transportation (quantum information), and ultra-fast data

processing (quantum computing), the rate-limiting factor in their application is processing of big data. The expected amount of time required to input data to enable computational modelling may not justify the ultra-fast processing aspect they offer. This is mainly due to a lack of quantum computers – there are currently what is called “the Noisy Intermediate-Scale Quantum Computers” (NISQ). However, NISQ has no error correction. The use of quantum computing is therefore currently not feasible for machine learning and other applications such as Grover and Monte Carlo simulations.

Despite these limitations, the use of quantum simulations and inspired optimization in the following cases will yield greater outcomes:

- Development of new materials for carbon capture as an example
- Tackling the spreading of antibiotics in wastewater
- Eco-friendly fertilizer production
- Sustainable and nutritious food production in a changing climate
- Optimizing vaccine distribution

Use of quantum systems simulations is therefore practical for quantum chemistry, quantum physics, material sciences and cryptanalysis.

Though quantum computing is not yet capable of machine learning, the computing systems that allow for this are bringing ground-breaking discoveries. In the global campaign to eradicate polio, a discovery of certain parts of the world that were not well mapped (e.g., unmapped villages in parts of Nigeria) and therefore not vaccinated were made through the evaluation of satellite images.² This was followed by a detailed study of the picture/geographical characteristics of that area (‘phenotyping’), which enabled a correlation that led to the identification of similar villages/areas in other regions that were also not mapped and not vaccinated.

3.2 | Drug development: Steve Kern

In the drug development processes, modelling is applied from discovery to confirmatory trials to make predictions/scaling for the next developmental phase and subsequent application of the product being researched. An example is the integrated application of modelling techniques from drug discovery through confirmatory clinical trials in the development of novel anti-malarial drugs.³ In the following discussion, malaria is used as an example for the potential benefits of cross-disciplinary networking.

The use of controlled human infection models in infectious diseases such as malaria is an example to facilitate the discussion. In these programmes, the volunteers are purposely infected with a pathogen to allow detailed studying and prediction/simulation of effective concentrations to clear the parasite.⁴ Such high-risk studies require well-thought-out simulations by specialized teams and, when successful, create the opportunity for improving the success of subsequent clinical pharmacology studies.

Additionally, with continuous technological progression of microfluidics, the use of physical in-silico models promises an expectation to minimize or eliminate the use of animals in preclinical studies. This

is a cross-disciplinary field involving the use of computational models to study clinical pharmacology, toxicology and pharmaceuticals.

The use of computing in this field is not only limited to direct the drug development processes, but can also be used to understand variability in drug responses when a drug is used in the field. An example of this is a study assessing the impact of malnutrition on children being treated for malaria by the WorldWide Antimalarial Resistance Network (WWARN).³⁰ In this study, aggregate data from clinical practice of children receiving malaria treatment with lumefantrine was used to assess for signs that could predict any failure of the therapy to clear the malaria infection. The results showed that when children are underweight for their age, there tends to be less success from normal dose therapy with lumefantrine compared to children of normal weight in the same age group. Even though underweight children received a larger mg/kg dose of the drug, the treatment was less effective which was associated with lower plasma concentrations for the given dose. This can be explained by the disrupted absorption in their digestive system due to malnutrition. Using modelling to understand these dynamics gives insights into how drug dosing can be adjusted for effective therapies across different patient populations. More elements can be added to the dimensionality of the model such as how the disease spreads in different geographies, how to simulate it in different levels of granularity, and, when coupled with epidemiological models, how to estimate the cost and effectiveness of the interventions.

3.3 | Health economic modelling: Johanna Lister

With the many effective health technologies available, modelling enables the identification of the most cost-effective interventions from which everyone should benefit. However, due to resource constraints, funding every health programme or intervention is not feasible. Mathematical modelling and simulation can address these limitations in the context of health technology assessments.⁵ The choice of which programme/interventions to pursue can be made using different social, ethical and other value judgements. Health economic (HE) modelling is often at the heart of such evaluation. HE makes the assessment through comparison of the cost required to provide the intervention compared with the outcome of the intervention across two or more technologies:

- Costs often taken into consideration include direct (e.g. cost of medicines, equipment/investigations such as X-ray, healthcare service provider) and indirect costs (e.g. related to lost time at work, school or caring for a sick family member).
- Outcomes commonly used include quality of life through a measure called quality-adjusted life-years (QALYs).

The results derived from these predictions can be used to support decision and policy making for allocation of limited resources. For example, a model framework has recently been developed using empirical data from randomized control trials (RCTs) in Tanzania and Uganda to compare the public health impact and cost effectiveness of

different malaria prevention measures currently in widespread use.⁶ The study confirmed the importance of taking local differences into account for decision making and that modelling outcomes can effectively support evidence-based decision making for investment in vector control of malaria.

During drug development, HE modelling is conducted in different phases. Its main role is in the late stages of development (phase II/III onwards), where economic evaluations are used to show the new drug's value for money towards reimbursement decision makers. Payers can then use this information to help allocate their scarce resources efficiently. Less common application of HE modelling takes place in the early development of drugs (preclinical up to phase II). Early modelling can be used to inform go/no go decisions and priority setting by the drug manufacturer, or optimal position of the product such as specific indication or sub-population of interest.

3.4 | Agriculture: Professor Patrick Noack

The example of the influence of malnutrition on the effectiveness of the anti-malarial lumefantrine highlights the inter-relations between public health, nutrition and agriculture. In this discipline, modelling techniques are applied for prediction and/or simulation of future agricultural outcomes such as prescription maps, detection of plant damage, faunal and/or weed detection, plant protection, seeding, etc. An example are plant breeding field trials which are conducted to enhance breeding progress by determining which breeds are suitable for certain climatic conditions, and which breeds are resistant to drought stress.⁷ The use of visual plant scoring during the phenotyping process is subjective, time-consuming, and cost- and human capital-intensive. Drones are therefore used to assess plant traits, lodging and characterization of different aspects that affect plant breeding. Drones can fly over large areas and thus avoid plant damage, enabling faster collection of required data. Machine learning algorithms are then applied to predict the future plant yield.

Drone technology has been used in West Africa to determine the areas where malaria is endemic.⁸ Farmers use remote sensing data to determine where water has accumulated in order to plan effective intervention strategies such as spraying to eliminate the mosquitos in those regions. This technology supports the restricted use of pesticides/chemicals which have a detrimental effect on the environment.

3.5 | Climate change: Georg Feulner

Reliable projections^{4,9, ch.} of future climate states (and thus also future agricultural yields and health impacts) are of particular importance in light of the current climate and ecological crisis.^{9,10} The Earth is a coupled interconnected system comprising the atmosphere, the oceans, the cryosphere and the biosphere, and Earth system models have to take this complexity into account, in particular to explore the connected pressures on different parts of the Earth system. In addition to and in combination with a wealth of observational data, these

models are important to improve our understanding of processes, interactions and feedback in the coupled Earth system, to be able to interpolate observational data, and to simulate past and future Earth system states.

Despite the complexity of the Earth system, the latest generation of Earth system models has reached a remarkable level of maturity, although several challenges remain.^{9, ch.1} Some of the challenges relate to the modelling of clouds, which remain difficult to model, with important implications for projected precipitation patterns and for feedbacks connected to clouds. Uncertainties in modelling these and other feedbacks in the Earth system also affect climate sensitivity, i.e. the global warming expected for a doubling of the atmospheric CO₂ concentration.^{9,11} Current developments mostly focus on increasing the models' spatial resolution and on machine-learning techniques; in addition model intercomparison projects and the use of faster models for ensemble tests remain important.^{12,13} Finally, it should be kept in mind that all state-of-the-art models are validated against observations in the modern-day period, with no guarantee that the models will be reliable also for future warmer climate states. One way of dealing with this challenge is the investigation of past warm climate states to test the models and thus increase our confidence in future projections.^{9,14, ch.1} This is also relevant with respect to the prediction/simulation of epidemiology outcomes and their potential treatment interventions. It should be noted, however, that the evidence for modern anthropogenic climate change does not rest on Earth system models, and that the models' remaining deficiencies are no excuse for the still insufficient emission mitigation measures.

Economic models have been developed to estimate the global health impacts of climate change.¹⁵ Based on this model, the estimated mortality risk associated with increased average annual temperatures ranges from 0.1% to 1.1% per 1 °C, depending on the global region. This study provides an example of how subject matter experts can work alongside climate economists in providing important information for decision and policy making.

3.6 | Epidemiology: Miriam Njoki Karinja

The importance of epidemiological modelling is to understand the patterns and dynamics of diseases within populations, as well as to examine the transmission of diseases, identifying risk factors, and assessing the impact of various interventions on the health of a population.

As an example, a model has recently been developed capturing heterogeneity in malaria transmission across Africa together with financial cost data for key malaria interventions. The most efficient ordering of interventions to reduce malaria burden and transmission were estimated, including long-lasting insecticide-treated nets, seasonal malaria chemoprevention or indoor residual spraying.¹⁶ The study demonstrated the cost-benefits of these interventions and their regional differences, as well as the need for novel interventions to achieve malaria eradication. In another study, human pharmacokinetic data, mortality data for mosquitoes and a malaria transmission model were combined to quantify the mosquitocidal effect of ivermectin and

to estimate the impact of ivermectin in combination with mass treatment strategies with artemether-lumefantrine on disease transmission. This study demonstrated the potential usefulness of the combined intervention.¹⁷

The recent COVID-19 pandemic was particularly instrumental in increasing collaborations and raising awareness on epidemiological modelling amongst the public and decision makers. For instance, concepts from epidemiological modelling, such as the reproductive number and shape of the epidemiological curve, entered mainstream conversation, extending beyond the scientific community. One of the simplest epidemiological models used to understand and predict the spread of disease, especially during the COVID-19 pandemic, is the SIR (susceptible, infected and recovered) compartmental model.^{18,19} In this model, the population is compartmentalized into three groups, namely: Susceptible (S), these are individuals who are not infected but can contract the disease; Infected (I), individuals who are currently infected and can spread the disease to the susceptible individuals; and Recovered (R), individuals who have recovered from the infection. The model is based on a set of differential equations that describe how individuals move between these compartments over time. During the COVID-19 pandemic, the SIR model was adapted in various ways to include additional factors such as asymptomatic carriers, individuals who have been exposed (E) or quarantined, and the impact of non-pharmaceutical interventions like social distancing and vaccination.

Other important variables like healthcare capacities need to be considered, especially during outbreaks that continue without control as they tend to exceed the healthcare capacity. Epidemiological modelling provides opportunities for cross-disciplinary collaborations, for example, on data visualization tools for effective communication of complex epidemiological models to policy makers and the public. There is also an opportunity for increased collaborations between epidemiologists, statisticians and data scientists amongst others, to bring a holistic approach to epidemiological modelling of complex health scenarios.

4 | CROSS-DISCIPLINARY COLLABORATIONS

Climate change affects agricultural outputs and the quality of agricultural products, which contributes to the (lack of and/or) overall nutritional well-being of a person. Food plays a major role in human pharmacology and in the overall management of any modified physiological state of a human.

The greenhouse gas effect not only has an impact on the pharmaceutical supply chain, such as drug storage conditions and other medication-related health impacts,²⁰ but climate change also affects the global distribution of human diseases,²¹ gene flow²² and the entire ecosystem.²³ For example, a group of researchers used temperature and rainfall data from satellites to predict the occurrence of cholera outbreaks due to the waterborne bacteria *Vibrio cholerae* across different regions in Yemen.²⁴ Using a machine-learning model,

the forecast of cholera outbreaks was 72% accurate on average, and up to 4 weeks in advance. A similar approach is used to study the distributions and patterns of antibiotic resistance, wherein a combination of weather data with waste-water surveillance for antibiotic-resistant genes is used to predict high-risk areas.²⁴ A previous modelling study has found a correlation between ambient temperature and antibiotic resistance in Europe.²⁶ At the centre of these various scientific disciplines, epidemiology serves as an enabling pillar for the clinical pharmacology discipline.

In this context, clinical pharmacologists experienced in modelling and simulations can assist with understanding of the disease conditions, their spread and progression patterns, etc.,³ as a basis for the study of drug therapies and/or health lifestyles. Health economists then carry out their modelling to determine the cost-effectiveness of interventions, and—in cooperation with other modelling communities—insight into geographical differences in drug effectiveness and impact of (novel) treatments. This information will assist in informing decision and policy making, for example by regulatory authorities and WHO prequalification.²⁵

5 | WHERE DO WE GO FROM HERE?

- *To understand how practitioners and researchers are using mathematical modelling in order to better understand if there are techniques that may be borrowed from other fields.* In the context of clinical pharmacology, it is essential to investigate how practitioners and researchers are employing mathematical modelling to enhance their understanding of drug behaviour, efficacy and safety. This exploration aims to identify innovative techniques from other scientific disciplines that could be adapted to improve pharmacological research and practice. By examining the methodologies and approaches used in fields such as engineering, physics and computational biology, we can uncover potential strategies that might be integrated into pharmacological modelling to achieve more accurate predictions and better therapeutic outcomes.³¹
- *In line with cross-disciplinary research methods, whether data from one field may be used to advance another research field.* Aligned with the principles of cross-disciplinary research, it is valuable to explore whether data and methodologies from one scientific field can be leveraged to propel advancements in another. This approach involves analysing the applicability and integration of data, tools and techniques across different domains to foster innovation and enhance research outcomes.^{26,27} By examining how insights from diverse disciplines can be adapted and utilized, researchers can unlock new potential for discoveries and improvements in various fields, including clinical pharmacology, biomedical sciences and beyond.
- *How do we line up the data from different models to facilitate the use/input across the different disciplines? How does our output become an input to other researchers' models?* To facilitate the seamless integration of data across various disciplines, it is crucial to establish standardized protocols for aligning data from

different models. This involves creating a common framework for data formatting, ensuring compatibility, and developing interoperable tools to bridge gaps between distinct scientific domains.³² By standardizing data inputs and outputs, we can enable researchers from different fields to utilize each other's models effectively. This collaborative approach allows the output from one researcher's model to serve as valuable input for another, fostering a more cohesive and interconnected scientific community. Consequently, this can accelerate innovation and lead to more comprehensive and robust findings across multiple areas of study.

- *How to share data.* It will be interesting to check how models across disciplines are structured and how they can be used in different fields. There are problems that other models across disciplines may be able to address and therefore should not be confined in silos. In the field of clinical pharmacology, there is a noticeable preference amongst researchers and practitioners for engaging in advanced modelling over handling the more tedious data management tasks.²⁸ This inclination towards modelling is understandable, as it offers the excitement of discovering new insights and driving innovation. However, it is crucial to recognize that the data aspects, although often less appealing, are fundamentally critical to the success of any modelling effort. Accurate, well-organized and secure data forms the backbone of reliable models and valid research outcomes. Therefore, it is essential to emphasize the importance of robust data management practices, ensuring that this critical element receives the attention and resources it deserves. By doing so, we can create a solid foundation that supports high-quality modelling and meaningful advancements in pharmacological research.
- *Data security.* Alongside advances, we also need to keep pace with appropriate protections. In the rapidly advancing field of clinical pharmacology, ensuring robust data security is paramount. As we harness the power of big data, artificial intelligence and other cutting-edge technologies to drive innovation in drug development and therapeutic strategies, it is critical to simultaneously implement stringent data protection measures.²⁹ Sensitive patient information, proprietary research data and clinical trial results must be shielded from unauthorized access and cyber threats. This involves employing state-of-the-art encryption methods, rigorous access controls and continuous monitoring of security protocols. By prioritizing data security alongside scientific advancements, we can safeguard the integrity and confidentiality of pharmacological data, fostering a secure environment that supports ethical research practices and maintains public trust. This dual commitment to innovation and protection is essential for the sustainable and responsible advancement of pharmacological science.
- *Data curation across the disciplines is critical so as to enable access and data-driven decision making.* The data curation process entails systematically organizing, managing and maintaining pharmacological data, allowing researchers and healthcare professionals to retrieve and analyse essential information easily. Additionally,

comprehensive data curation practices enable the identification of gaps in existing pharmacological research, highlighting areas that require further investigation and development. Data curation improves the quality and reliability of pharmacological data but also drives innovation and progress in drug discovery, development and clinical practice.

The question now is whether there are any efforts to bring together all these disciplines as there is close inter-dependence of occurrences amongst them, to remove the silos, reduce duplicated efforts in building models in each discipline and collaborate for robust and comprehensive models. There are some areas where cross-disciplinary collaboration seems immediately necessary. For example, outbreak prediction and response serve as the epitome of cross-disciplinary collaborations in modelling. The health effects from heat-waves/global warming are visible, both in humans and in the agricultural field. This symposium has allowed representatives from different scientific disciplines to share and consider the 'what if' modelling experiments across their fields of expertise to close the gaps and implement integration strategies. Machine learning could be a good first step in putting all the data available from different silos on similar/inter-related research questions to assess if better, well-integrated results may be derived from this. A great start will be enabling access to these great technology advancements.

In summary, the speakers and panellists engaged in a robust discussion which addressed the following key aspects:

- Limitations in current approaches as exemplified by challenges with inadequate computing resources to fully integrate multi-scale models across these domains.
- Modelling of uncertainties as illustrated by the Earth system modelling of clouds with implications for climate projections and understanding feedback in the coupled Earth system. Further, the current state-of-the-art Earth system models are validated in the modern-day period and their reliability cannot be guaranteed for future warmer climate states.
- Maintaining credibility whilst recognizing the limitations as demonstrated by the HE modelling, which is mainly applied in the late phases of drug development to aid in decision making. If it was feasible to also apply this modelling in the early stages of development, it would further support decisions to not pursue any developments that may prove futile in the later stages and optimize the resource allocation. Earth system modelling is another example.
- Communicating increasingly complex modelling processes with decision makers, colleagues in other disciplines or the public. The COVID-19 pandemic provides a good example, whereby complex models used by different disciplines were applied to strategize the management and containment of the pandemic, adopted and carried out by key stakeholders and the public as a result of effective communication.
- Difficulties in getting the right inputs—data sets, clean data, reliable data, real-world data. This is demonstrated by the quantum

computing limitations for processing of big data since the availability of quantum computing raised hopes for ultra-fast data processing with more efficient modelling tools.

- Long-term nature of some data collection and analyses as illustrated by the use of machine-learning models to predict the outbreak of cholera and antibiotic resistance patterns and distributions.
- Attracting and inspiring the next generation of modellers as exemplified by the symposium, and a need to consolidate data from different silos on similar or inter-related research questions for better and well-integrated models through access to technological advancements.
- Creating a forum where cross-disciplinary networking can begin as demonstrated by this symposium which allowed representatives from different scientific disciplines to share the modelling experiments from their respective fields of expertise and deliberate on future integration strategies.

6 | CONCLUSIONS

The insights shared during the discussions made it quite clear that there are significant inter-links across various scientific disciplines, and the mathematical models used in these disciplines, though carried out in silos, are similar, relevant and applicable to all of them. Cross-disciplinary networking between modelling communities can provide a holistic approach to a variety of interconnected problems. The one discipline that seamlessly integrates these disciplines is clinical pharmacology. For more efficient and cost-effective interventions to be developed for individuals, communities and various populations, a multi-faceted approach is required. Challenges, especially in low- and middle-income regions such as Africa, include scientific gaps, data gaps and data access, and modelling and forecasting gaps. These can be overcome by capacity building, knowledge management and communication.

AUTHOR CONTRIBUTIONS

Bernd Rosenkranz, Goonaseelan (Colin) Pillai, Tirhani Maluleke, Rohan Benecke, Sunday Oladejo, Gabriel McClelland and Kanshukan Rajaratnam planned and organized the symposium. The Symposium Chairs were Rohan Benecke and Kanshukan Rajaratnam and the Symposium Moderator was Catriona Waitt. Gabriel McClelland was the Technical Director. The speakers were Georg Feulner, Steve Kern, Johanna Lister, Miriam Njoki, Patrick Noack and Francesco Petruccione. Tirhani Maluleke wrote the original draft and all the authors reviewed and edited the manuscript.

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COMPETING INTERESTS

We do not have any conflicts of interest to declare of relevance to this symposium report.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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How to cite this article: Maluleke T, Benecke R, Oladejo S, et al. Cross-disciplinary mathematical modelling to benefit healthcare – could clinical pharmacology play an enabling role? *Br J Clin Pharmacol*. 2024;90(10):2509-2516. doi:[10.1111/bcp.16192](https://doi.org/10.1111/bcp.16192)