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Harnessing Genomics for Antimicrobial Resistance Surveillance 5

Innovations in genomic antimicrobial resistance surveillance

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Whole-genome sequencing of antimicrobial-resistant pathogens is increasingly being used for antimicrobial resistance (AMR) surveillance, particularly in high-income countries. Innovations in genome sequencing and analysis technologies promise to revolutionise AMR surveillance and epidemiology; however, routine adoption of these technologies is challenging, particularly in low-income and middle-income countries. As part of a wider series of workshops and online consultations, a group of experts in AMR pathogen genomics and computational tool development conducted a situational analysis, identifying the following under-used innovations in genomic AMR surveillance: clinical metagenomics, environmental metagenomics, gene or plasmid tracking, and machine learning. The group recommended developing cost-effective use cases for each approach and mapping data outputs to clinical outcomes of interest to justify additional investment in capacity, training, and staff required to implement these technologies. Harmonisation and standardisation of methods, and the creation of equitable data sharing and governance frameworks, will facilitate successful implementation of these innovations.

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Background

In early 2022, the Surveillance and Epidemiology of Drug Resistant Infections Consortium (SEDRIC) held a series of workshops to map the current and future landscape of genomic antimicrobial resistance (AMR) surveillance. Although genomics has already begun to complement or replace phenotypic, immunological, and molecular approaches to isolate-based surveillance, recent innovations in genomic technologies promise to improve surveillance and epidemiology of AMR further. These developments will allow for tailoring of AMR interventions in real time, and address some of the barriers that impede widespread implementation. Held on May 5, 2022, the fourth workshop focused on innovations in genomic AMR surveillance, and brought together stakeholders to conduct a situational analysis and reach a qualified consensus on the use of several predefined innovations for the surveillance and monitoring of AMR. Innovations were identified on the basis of proven benefits in research and a lack of implementation in routine surveillance. The innovations selected were clinical metagenomics, environmental metagenomics, gene or plasmid tracking, and machine learning. Through discussions on the benefits, barriers, and potential implementation pathways for these approaches, we identified common challenges that need to be addressed to enable the integration of these innovations with genomic AMR surveillance systems.

Clinical metagenomics

Metagenomics is the study of genetic material directly from environmental or clinical samples, without the need for isolation or laboratory cultivation of individual organisms. For the purposes of the workshop, clinical metagenomics was used as a broad term encompassing any approach that aims to analyse all genetic material from microorganisms and their hosts in clinical samples.[1] This approach is achieved through next-generation sequencing (NGS) and aims not only to detect potential pathogens, but also to enable an understanding of the host, the microbiome, and host–microbe interactions.

Clinical metagenomics offers multiple advantages for AMR surveillance over traditional laboratory culture and single-isolate sequencing approaches. Removing the need to culture an isolate has the potential to enable much faster diagnosis and the detection of as-yet-uncultured pathogens.[2] These approaches have the potential to generate robust causal and phenotypic information in clinically relevant turnaround times (hours rather than days) and could, therefore, increase the uptake of genomic AMR surveillance on the clinical front line (figure). Metagenomic data can also enable the detection of infections caused by multiple strains (polyclonal) and species or pathogens (polymicrobial),[3] and lends itself to the discovery of unexpected or previously unknown pathogens[4] and pathogens not subject to routine surveillance. Additional benefits include the ability to identify and characterise all antibiotic resistance genes in a sample,[5] determine reservoirs for resistance,[6] provide real-time reporting of resistance elements during sequencing,[7] and identify individuals at risk.[8]

Analysing metagenomic data in a clinically meaningful way can be challenging owing to complexities in accurately predicting AMR phenotypes,[9] achieving enough sequencing depth to comprehensively detect resistance determinants,[10] and correctly assigning the origin of metagenomic reads to a microorganism in the sample,[11] which is particularly challenging when a resistance

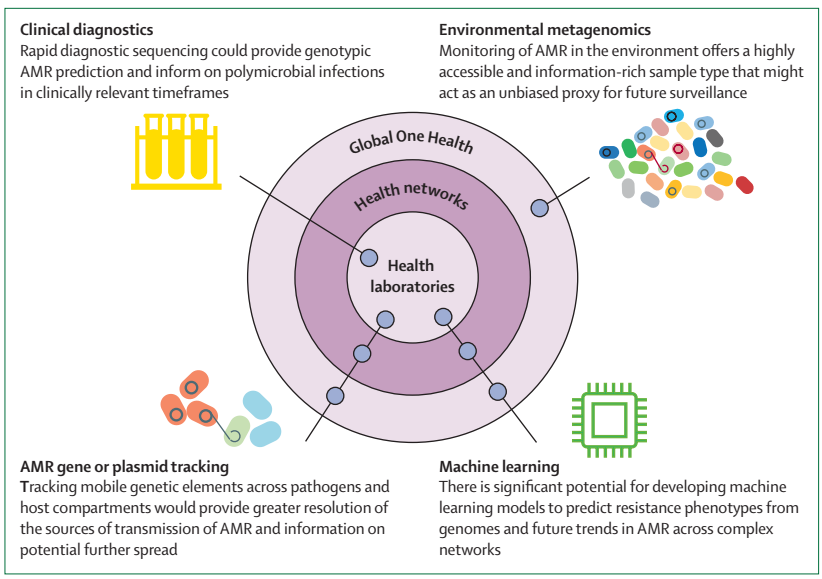

Figure: **Incorporating innovations in genomic AMR surveillance**
Four genomic innovations and AMR surveillance domains that could be positively affected by their realisation, indicated by dots overlaying the lines intersecting with the central schematic of the nested surveillance domains. AMR=antimicrobial resistance.

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mechanism is carried on a plasmid. Public datasets will be essential for clinical metagenomic analyses because they allow baseline trends and patterns to be established, against which samples can be compared. However, there are currently large representation gaps in these sources of data.[12] Consequently, the implications of finding under-represented populations of bacteria present in a sample are hard to determine, and require expertise to interpret. Data coordination is also inherently challenging on a global scale, with geopolitical sensitivities presenting challenges to routine data sharing.[13] These challenges mirror the representation and data governance issues identified in the second, third, and fourth papers in this Series[14–16]). Additional barriers include technical issues around methodology and reproducibility, such as standardising controls between datasets and the handling and automated processing of large datasets, as well as accessing funding, data storage, and resources for analysis, all of which vary by geographical region. As highlighted for isolate-based genomic AMR surveillance in the second, third, and fourth papers in this Series,[14–16] certain barriers to implementation (eg, training, infrastructure development, and maintenance) are likely to be particularly challenging to meet in low-income and middle-income countries.

Improvements in frameworks, databases, and software are needed to address challenges in the biological interpretation of raw metagenomic data. Regional differences in funding and coordination create barriers that can be mitigated by developing models in which routine metagenomic sequencing might begin at regional hubs before being disseminated to local and national spoke laboratories. Such models enable retention of the support and benefits of large regional hubs (eg, centralised training and individual skillset development), while eventually permitting a more tailored approach at the local level, similar to that outlined for isolate-based surveillance (see the first paper in this Series).[17] Although we should ensure that training provision is guided by geographically tailored blueprints to ensure that individuals are trained in using the tools and approaches available to them, wherever possible it will also be important to develop standard methods, such as the use of mock communities during laboratory pre-processing and sequencing,[18] and the use of well characterised and robust pipelines for bioinformatic analysis.[19] However, it should be acknowledged that certain aspects of standardisation are not always feasible across all locations (eg, the type of sequencing technologies available). Additionally, limited standardisation across databases adds further complexity. For example, although the National Database of Antibiotic Resistant Organisms possesses a higher number of acquired resistance genes, the Comprehensive Antibiotic Resistance Database provides better coverage of mutation-conferred resistance.[20] As such, training for competency in varied approaches for genomic analysis and epidemiology will be crucial to success in clinical settings and clinical care of infectious disease cases, as is true for the other domains covered by the working group. This training will also be vital in facilitating infrastructure development to enable both country-level self-sufficiency and international collaboration.

Environmental metagenomics

Sequencing of genetic material from environmental samples—known as environmental metagenomics[21]—creates opportunities to better understand the niches, reservoirs, and transmission routes of antimicrobial-resistant bacteria. It also holds promise as a tool to monitor the impact of public health measures (figure). Environmental samples make it possible to survey overall levels of AMR, including carriage among the healthy, non-symptomatic population, and are comparatively accessible, which is particularly valuable in settings where access to health care is less equitable. Furthermore, environmental metagenomics is culture-independent, and might function as an early warning of AMR yet to be observed in clinical isolates.

However, sample sources for environmental metagenomics can be highly variable. For AMR surveillance in a One Health context, surveillance of sources such as wastewater, waterways, farms, and air can all provide valuable information on the flow of AMR within and between potential reservoirs[22,23] (see the fourth paper in this Series[16]). For example, wastewater sampling has been successfully used in the surveillance of a number of infectious diseases and public health threats.[24,25] Experience from the COVID-19 pandemic[24] has indicated that community wastewater surveillance can be an important supplement to hospital case

reporting, which—although not a perfect proxy for population incidence—corresponds well with infection trends and incidence data.[26]

Difficulty in resolving gene–pathogen relationships, determining viability, and quantifying abundance (or relative abundance) challenge the interpretation and actionability of environmental metagenomic surveillance data.[6] However, recent genomic approaches offer the promise of overcoming some of these challenges; for example, metagenomic chromosome conformation capture technologies have the potential to allow the attribution of plasmids to their hosts in metagenomic samples through physically linking plasmids to the chromosomes of their hosts.[27]

Epidemiological interpretation of a single environmental sample is fraught with difficulty.[28] For environmental metagenomics to be most effective, long-term funding (a minimum of 10 years) and implementation will be needed to establish baseline rates and diversity of AMR in a given environment (eg, wastewater), track trends, and identify disruptions in these patterns across harmonised sampling frameworks. Analysis workflows are also required to enable comparison across settings. Understanding the uncertainties and variability in environmental samples,[29] which stem from multiple stochastic and systematic sources, will be crucial to fostering confidence in the utility of the datasets. Establishing sample archives now (eg, biobanking), which can be analysed with future pipelines, will be crucial to understanding and interpreting environmental metagenomic data over time. Effective data-management processes and systems, including data storage, transfer, and sharing, must also be developed. Of note, clarity and consistency on the ethical and regulatory implications regarding the handling of human reads found within environmental samples is vital to enable the sharing of this data.[30]

The use of environmental metagenomics for AMR surveillance has, so far, largely been confined to the research domain,[6] and a lack of political will to invest in advancing this technology into active surveillance or monitoring was identified as a barrier to its future use, although this picture is changing. The best ways to apply these approaches as a surveillance tool are not yet well understood, and we have not yet evaluated the additional information provided over traditional clinical surveillance measures versus the time and cost of more comprehensive environmental surveillance. Researchers must generate successful use cases that show proportionate, cost-effective, and timely actionable insights that correlate with indicators relevant to clinical or public health, or both.

Defining a purpose (eg, early warning or monitoring of control measure success), harmonisation of sampling and analysis processes, and validation are all areas where consensus is needed for progress to occur. Establishing this consensus will require long-term partnerships between researchers and policy makers to align surveillance efforts with data needed to inform concrete actions that address AMR. Establishing global leadership to maintain a long-term vision and highlight the potential importance of the environment in AMR is a key area for advocacy, which could lead to embedding environmental surveillance within AMR action plans and disrupting current research silos.

Gene-based and plasmid-based tracking

Tracking AMR genes or the mobile genetic elements that carry them (rather than, or as a complement to, the pathogen lineages in which they reside) offers several advantages for enhancing AMR surveillance. Targeted sequencing of AMR genes and plasmids can provide clearer insights into the presence,[31,32] emergence,[33,34] and direction[35–37] of transmission of AMR among different ecological compartments (eg, human and animal, or hospital and community), individual hosts, and microorganisms than that provided by metagenomic surveillance or isolate-based sequencing (figure). Gene-based or plasmid-based tracking can aid in assessing the risk of critically important resistance mechanisms moving between compartments—eg, from humans to animals or the inverse.[38] It can also determine the means by which AMR spreads, whether by a small mobile genetic element such as a transposon, a larger mobile genetic element such as a plasmid, or a chromosomally integrated gene, which can be used to anticipate dissemination patterns among bacterial populations.

Plasmid monitoring can function across all One Health sectors: at a local level for outbreak detection,[36,39] and at a national and global level for surveillance and larger contextual understanding.[40,41] Tracking plasmid backbones of concern, even when they do not carry AMR genes, is key to understanding plasmid epidemiology and identifying high-risk settings before an AMR gene is acquired. Similarly, tracking the presence of AMR genes in non-pathogenic bacteria will reveal the flow of AMR genes through different reservoirs, including the environment.[42] Consideration must be given to how existing risk-assessment frameworks based on single-isolate models can be adapted to mobile cassette or plasmid transmission. Mathematical modelling to establish the minimal sampling required[43] and cost-effectiveness studies would help justify the cost of targeted gene and plasmid monitoring.

Tracking of AMR genes and plasmids currently relies on a range of sequencing technologies and platforms that have different requirements for consumables and offer specific benefits and limitations. Although short-read sequencing currently dominates AMR surveillance, long-read sequencing that produces more complete plasmid sequences has the potential to offer more detailed insights into plasmid epidemiology.[44] Lessons can be transferred from the metagenomics community on how to standardise and harmonise different methods.[45] The working group noted that from an implementation perspective, a single composite

genomics platform that would deliver complete genomes sufficient for resolving AMR context with a throughput comparable to short-read technologies would be ideal.

Defining plasmid similarity and classification can be challenging, especially for plasmids with highly plastic sequences. Nomenclature standardisation and identification of plasmid characteristics, including their individual structure, would benefit these efforts. Building on the National Collection of Type Cultures[46] and American Type Culture Collection,[47] institutional and stakeholder endorsement of a physical set of standardised plasmids from clinical, environmental, and animal samples would allow for platform and phenotype benchmarking.

Improving the interpretability of plasmid surveillance data by linking plasmid characteristics with health outcomes in human and animal hosts is a priority for future research. We must better characterise plasmid diversity,[48] transmission rates,[49] permissiveness,[50,51] stability,[50,51] and other phenotypes.[52] Epidemiological data can be used as a starting point and as a supplement to investigating the clinical and public health risk of plasmids, but a better understanding of plasmid biology will allow researchers and public health bodies to produce increasingly accurate databases[53,54] and tools[55,56] to better define and describe plasmids and their associated AMR risk.

Machine learning

Machine learning is a subfield of artificial intelligence that focuses on enabling computer systems to learn from, and make, decisions based on data. The goal of machine learning is to create systems that can autonomously improve their accuracy and performance over time, without being explicitly programmed to do so. Machine learning tools for the analysis of large, diverse, and often complex data streams have improved a great deal over recent years,[57] creating an opportunity to improve genomic AMR surveillance through the integration and analysis of different data streams. We highlight two such use cases.

The first application is the use of machine learning to predict AMR using genomic and antimicrobial susceptibility testing (AST) data (figure). The advantages of adopting machine learning approaches include identifying novel resistance mechanisms,[58] predicting AMR from incomplete data (eg, metagenomics),[59] and modelling the interaction between resistance mechanisms.[58] However, several challenges exist in translating promising preliminary work in this area into public health benefits. Large, internationally representative datasets of high-quality phenotypic AST data are required to develop accurate machine learning algorithms.[60] Quantitative minimum inhibitory concentration data are more easily combined and compared than categorical sensitive, intermediate, and resistant (SIR) data owing to the breakpoints between categories and conventions changing over time,[61] but are less commonly made available to the research community. Centralised AST tends to produce more consistent phenotyping results, but distributed international capacity for AST coupled with external quality assessment would enable more sustainable and equitable data generation.[62,63] Good model training data should have an even representation of sensitive and resistant isolates, and of different resistance mechanisms, a distribution unlikely to be captured by a standard surveillance sampling framework. In the future, algorithms would ideally be independently benchmarked against a shared set of test isolates that are changed regularly to capture new AMR mechanisms[64] and prevent overtraining of algorithms to the test data. A valuable adjunct to standard surveillance sampling frameworks would be to preferentially sequence treatment failures and rare resistance phenotypes to enrich for potentially novel resistance mechanisms.[65]

The second promising application of machine learning to AMR surveillance is the use of forecasting tools to measure and predict changes in resistance rates over time and space.[66,67] Models can be trained to predict resistance rates based on historical prevalence data and identify unexpected fluctuations in resistance that might reflect a successful intervention or a concerning new trend. However, heterogeneous data obtained at different scales is difficult to integrate.[68] Fine scale data, such as monthly AST data broken down by postcode, is ideal,[66] but increased granularity in surveillance poses greater privacy concerns. These concerns could be addressed by providing restricted access to data, similar to Global Initiative on Sharing All Influenza Data[69] and the UK Biobank.[70] Another limitation of current models is that there is little or no integration of the mechanisms causing AMR in the modelling process.[71] This integration could be achieved by integrating other data sources, such as gene or plasmid tracking, antimicrobial use, or human and animal movement data, or a combination of these.[67]

Several general challenges in the application of machine learning to AMR surveillance were identified. Machine learning algorithm accuracy can degrade over time following deployment.[72] Existing training datasets are biased towards a small number of high-income countries, making it probable that algorithms will perform better in these settings and might falter in different locations or over longer time periods. As such, these surveillance tools should be regularly validated against traditional surveillance data to evaluate their robustness.[73] Successful deployment and translational impact of machine learning for AMR surveillance will require bringing together experts and stakeholders from different disciplines from the conception of a project to its deployment. But the development of machine learning for health is still, to a large degree, undertaken in silos, without the integration of knowledge and expertise available from other fields of application.[74] Using

community platforms such as Kaggle or CAMDA could improve the interaction between the machine learning community and stakeholders to identify key challenges and describe robust solutions.

Recommendations from the working group

Several key themes emerged when discussing potential innovations in genomic AMR surveillance. First, funding and political will are key requirements for the implementation of technological innovations in AMR surveillance, across regional, national, and international scales. A proposed concrete step for engaging funders and policy makers was for researchers and public health organisations to provide clear use cases where these innovations add demonstrable value, and present a thorough economic assessment of the costs versus benefits of investing in additional capacity. Ultimately, a long-term strategy and supporting funding and infrastructure are needed to realise the potential of innovations in genomic AMR surveillance.[9] In the long term it will be important to harmonise these strategies on multiple levels: globally, by working with key partners such as WHO; nationally, by working with governments and public health providers; and locally, by working with health professionals familiar with local needs and priorities.

Second, introducing innovative technologies and data streams requires training, capacity building, infrastructure, and collaboration to provide actionable insights. The successful translation of innovations requires multidisciplinary stakeholder involvement from the initiation of a project (eg, choosing a problem to address) to the deployment and maintenance of an effective surveillance system. Involvement of stakeholders (from research, industry, public health, and policy) from across the One Health landscape is also needed to ensure data can be integrated and compared in a meaningful way, and to avoid duplication of efforts. Harmonisation and standardisation of methods and overcoming technical challenges are still required to get the best use out of these innovations. Importantly, it will be vital to map how well these data streams correspond to outcomes of interest, such as clinical infection incidence and disease outcomes, to justify the additional investment in capacity, training, and staff.

Data governance challenges must also be addressed. For example, human reads in metagenomic sequencing pose potential privacy concerns. Consensus guidelines on addressing these concerns should be established. The availability of representative data for training machine learning algorithms is also a challenge, particularly where providers of the data might be risking potential reputational damage (eg, in the food industry), or reduction of their research competitiveness.

Agreement on sampling frameworks and standards for data quality and sharing for denominator populations (which illustrate the baseline frequency of an AMR mechanism of interest) is needed, particularly for environmental and plasmid monitoring. These frameworks could be modelled from existing frameworks, such as the European Food Safety Authority harmonised monitoring of AMR[75] or the UK Veterinary Antimicrobial Resistance and Sales Surveillance frameworks.[76] Part of achieving this agreement will be resolving a core tension between standardising genomic AMR surveillance practices globally and tailoring approaches to provide cost-effective solutions to local problems. Tiered models of adopting genomic AMR surveillance at different price points are a good example of a strategy for addressing these tensions.[63]

Conclusions

Moving to more technically sophisticated AMR surveillance will improve human and animal health, provided that the approaches focus on solving the right problem, produce actionable data, and can be integrated into existing systems. To achieve this transition, researchers must provide clear evidence of the marginal utility of these innovations. The innovations discussed here are likely to function as a complement to some degree of ongoing isolate-based surveillance, rather than a replacement. Each of these innovations relies on high-quality reference data produced from whole-genome sequencing and phenotyping of single isolates. Each innovation offers potential improvements in surveillance relative to isolate-based sequencing, either by allowing analysis of many isolates at once across multiple ecological compartments, allowing targeted tracking of AMR mechanisms of interest at a lower cost, or enabling the analysis of data at a scale and speed not achievable by other approaches.

While nations work to translate these methods from research to practice, technical innovation continues. Promising developments, such as on-site sequencing that dynamically enriches and depletes specific sequences,[77] rapid point-of-care AMR diagnostics,[78] and automated literature mining for novel AMR mechanisms,[79] might play important roles in the future. To achieve ongoing enhancements, it is essential to provide platform-agnostic support for integration as outlined in the recommendations from the working group (see the first paper of this Series[17]). By implementing these strategies, we can proactively enhance AMR surveillance and effectively confront the challenges presented by antimicrobial resistance.

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Contributors

SJP, NAF, KSB, EJ, JGN, JTM, and NEW conceptualised this Series paper. KSB, EJ, and JGN curated the data. KSB, EJ, and JGN did the formal analysis. SJP, NAF, JGN, and JTM acquired funding. SJP, NAF, KSB, EJ, JGN, JTM, and NEW did the investigation. SJP, NAF, KSB, and EJ developed the methods. SJP, NAF, KSB, EJ, JGN, and JTM were responsible for project administration. SJP, NAF, NEW, KSB, and EJ were responsible for supervision. KSB prepared the original data visualisations. NEW, VP, EC-O, KKT, EJ, and KSB wrote the original draft. All authors reviewed and edited the paper, and engaged and participated in the workshop.

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