

Editorial

# ***In Silico* Technologies Advancing Microbial Science: A Visionary Review**

Lutfun Nahar<sup>1,2</sup>

<sup>1</sup> Centre for Natural Products Discovery, School of Pharmacy and Biomolecular Sciences, Liverpool John Moores University, Byrom Street, Liverpool L3 3AF, UK; profnabar@outlook.com

<sup>2</sup> Laboratory of Growth Regulators, Palacký University and Institute of Experimental Botany, The Czech Academy of Sciences, Šlechtitelů 27, 783 71 Olomouc, Czech Republic

Received: 2 December 2025; Accepted: 16 December 2025; 5 January 2026

**How To Cite:** Nahar, L. *In Silico* Technologies Advancing Microbial Science: A Visionary Review. *eMicrobe* **2026**, 2(1), 4. <https://doi.org/10.53941/emicrobe.2026.100004>

The transformative impact of *in silico* methodologies on microbiology and infectious disease research has been authoritatively articulated in the inaugural editorial of *eMicrobe* [1]. The present commentary reflects upon this vision and illustrates its realisation through recent exemplary studies.

## **1. The Computational Redefinition of Microbiology**

High-throughput sequencing, pangenomic analysis, machine-learning-enabled surveillance systems, and multi-omics convergence have rendered traditional reductionist approaches insufficient. These technologies are now regarded as foundational rather than supplementary to microbial discovery and clinical translation [1].

## **2. Integrated Bioinformatics Pipelines**

A fully containerised, modular pipeline (MIntO) that performs paired metagenomic-metatranscriptomic analysis while preserving sample identity has been developed. This approach enables simultaneous taxonomic profiling, functional potential assessment, and active gene-expression quantification, yielding biologically coherent insights unattainable through separate analyses [2].

## **3. Machine Learning for Precision Diagnostics and Risk Stratification**

Harmonised multi-cohort frameworks employing recursive feature elimination and ensemble learning have achieved area-under-the-curve values consistently exceeding 0.90 in predicting inflammatory bowel disease from gut microbiome data [3]. Similarly, gradient-boosting and recurrent neural network models applied directly to raw genome assemblies have attained >98% accuracy in identifying carbapenemase-producing Enterobacterales from clinical isolates [4].

## **4. Artificial Intelligence and Deep Learning in Biomarker Discovery**

Deep-learning architectures, particularly graph neural networks and transformers, have been demonstrated to substantially outperform classical statistical methods in identifying robust gut microbiota biomarkers across metabolic, oncological, and neuropsychiatric disorders [5]. Multimodal neural networks integrating amplicon, shotgun, and host phenotypic data have further enabled personalised dietary interventions that significantly improve postprandial glycaemic control [6].

## **5. The Gut Microbiome as a Systems-Level Metabolic Entity**



The gut microbiota is increasingly conceptualised as a dynamic metabolic organ whose myriad small-molecule effectors orchestrate systemic immunological, neurological, and xenobiotic responses. Contemporary *in silico* reconstruction of community-wide metabolic networks now permits prospective identification of taxa driving short-chain fatty acid synthesis, tryptophan catabolism, and secondary bile-acid biotransformation [7].

## 6. Clinical Translation and Persisting Barriers

Although 87% of surveyed European infectious-disease clinicians anticipate genomic methods becoming routine within five years, critical deficits in bioinformatics standardisation, workforce training, and reimbursement mechanisms remain [8]. Clinical metagenomic next-generation sequencing currently delivers diagnostic yields of 30–70% in culture-negative infections; however, widespread adoption continues to be impeded by high costs, prolonged turnaround times, and interpretative complexity [9].

## 7. Reproducibility, Openness, and Data Sovereignty

Irreproducible findings stemming from opaque preprocessing and non-deposited code are now recognised as a profound threat to microbiome science. Universal adoption of FAIR-compliant repositories, immutable containerised workflows, and standardised metadata schemas has therefore become imperative [10].

## 8. Predictive Modelling in the Post-Pandemic Era

Nationwide primary-care cohorts encompassing >4 million patients have been utilised to develop externally validated models revealing sustained 18–34% increases in antimicrobial-resistant community-onset infections attributable to pandemic-related disruptions in care delivery [11].

## 9. Global Equity and Open Science

Low- and middle-income countries, despite bearing >80% of the global infectious-disease burden, contribute <5% of microbiome publications. Open-access publishing, cloud-native analysis platforms, and distributed training initiatives are thus ethical and scientific imperatives [12].

## 10. Strategic Priorities for the Decade Ahead

Immediate priorities include seamless multi-omics integration with electronic health records, regulatory acceptance of explainable artificial-intelligence frameworks, internationally harmonised benchmarking standards, and systematic incorporation of computational literacy into microbiology curricula [1].

## 11. Conclusions

A compelling vision has been articulated in which computational rigour is fused with clinical relevance, openness with disciplined innovation, and global equity with scientific excellence [1]. By serving as the premier international platform for advancing this integration, *eMicrobe* invites researchers, clinicians, bioinformaticians, and data scientists worldwide to shape the next epoch of microbial scholarship.

## Funding

Lutfun Nahar gratefully acknowledges the support from the European Regional Development Fund (Project ENOCH #CZ.02.1.01/0.0/0.0/ 16\_019/0000868) and the Czech Science Foundation (Project #23-05474S).

## Conflicts of Interest

The author declares no conflict of interest.

## Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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