NATURAL LANGUAGE PROCESSING USING DEEP LEARNING: A COMPREHENSIVE REVIEW OF MODELS, TECHNIQUES, AND FUTURE DIRECTIONS

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ABSTRACT
Natural language processing (NLP) has emerged as a key focus of AI research for the analysis, interpretation, extraction, summarisation, and generation of human language. The vast amount of unstructured textual data in scientific research, electronic health records, clinical notes, radiology reports, public health documents, and digital health platforms has driven the demand for sophisticated computational tools and techniques capable of extracting structured and actionable knowledge from language. NLP has been greatly advanced by deep learning, which allows for automatic representation learning, understanding context, modeling sequences, and generating large amounts of language by means of structures like CNN, RNN, LSTM, GRU, attention mechanisms, transformers, and large language models. This review aims to present a detailed overview of deep learning-based NLP models, methods, applications, challenges, and future directions, focusing on biomedical informatics, clinical text mining, digital health and biomathematical relevance. It has numerous applications such as biomedical literature mining, named entity recognition, relation extraction, clinical decision support, pharmacovigilance, radiology report generation, public health surveillance, and construction of knowledge graph. The specific focus lies in the application of NLP to identify biological entities, clinical variables and quantitative evidence that can be used to support biomathematical modeling. There are several current challenges such as domain shift, privacy, hallucination, bias, interpretability, and reproducibility. The success of future progress relies on reliable, comprehensible, domain specific and clinically verified NLP systems.

KEYWORDS: Natural language processing, Deep learning, Biomedical informatics, Clinical NLP, Biomathematical modelling, Large language models

1. INTRODUCTION
One of the most significant fields of AI, natural language processing (NLP) allows computational systems to process, interpret, classify, extract, summarise and generate human language. Digital text has seen an explosive growth in the science, clinical, biomedical, social media, public health, and electronic communication industries, and requires automated approaches to transforming unstructured text into meaningful and analyzable scientific content. The traditional methods of computational methods could not adequately represent linguistic ambiguity, semantic variation, context and domain-specific terminology. However, recent developments in machine learning and deep learning have greatly enhanced the ability to harness complex linguistic patterns directly from vast amounts of data in textual form. Due to this, NLP has been used in various applications, including information retrieval, document classification, named entity recognition, sentiment analysis, machine translation, question answering, text summarization, and automated decision support (Bharadiya, 2023; Chen et al., 2024).

The advent of deep learning has been a significant milestone in the development of NLP. Previous NLP systems were dependent on hand-crafted features, linguistic rules, dictionaries and statistical hypotheses. While these methods made significant strides, they faced several challenges, such as scalability, contextual understanding, and generalizing to different domains. Unlike deep learning models, however, they require the pre-extraction of hierarchical language representations from text, which is still a time-consuming process. NLP systems have made significant advancements in understanding the syntactic structure, semantic relationships, long-range dependencies, and contextual meaning of text, thanks to the development of neural architectures like convolutional neural networks, recurrent neural networks, long short-term memory networks, gated recurrent units, attention-based models, and transformer architectures. This evolution has led to the emergence of NLP from feature engineered pipelines to increasingly complex end-to-end learning systems that can undertake increasingly complex language understanding and generation tasks (Sarker, 2021; Taye, 2023).

In biomedical, clinical and healthcare settings, there is enormous amount of knowledge in unstructured textual information in need of retrieval. The critical information in biomedical research articles, clinical notes, EHR, radiology reports, pathology reports, drug labels, clinical trial records, discharge summaries, and public health communications include information about diseases, symptoms, treatments, genes, proteins, adverse drug reactions, patient outcomes, and biological mechanisms. Much of this information, however, is in free text and so it is hard to systematically analyze with the more common quantitative methods. Deep learning-based NLP offers a computational connection between the unstructured biomedical language and the structured scientific knowledge, which includes biomedical entities, clinical events, semantic relationships, and evidence patterns. This makes NLP particularly pertinent to biomedical informatics, clinical decision support, drug safety monitoring, disease surveillance and biological knowledge discovery (Houssein et al., 2021).

The value of structured knowledge of biological mechanisms, clinical variables, disease course, drug effects, and population trends to mathematical and computational models makes NLP an increasingly important methodological tool in biomathematics. Such data can be spread out across biomedical text and clinical records. Deep learning based NLP can be used to recognize variables, uncover biological interactions, find disease-drug or gene-disease interactions, and organize textual data into a form for mathematical modelling. For example, text-based information could be used to construct disease networks, knowledge graphs, epidemiological models, pharmacological models and systems biology models. As such, NLP can not only be a language processing tool, but also a technology that can empower quantitative biology, computational medicine and data-driven biomathematical modelling.

The NLP field has been further extended by the use of transformer-based language models and large pretrained models. These models have proven good in language understanding, language generation, question answering, summarization and domain adaptation. They have shown that they can learn representations of context from large text corpora, making them particularly useful for specialized domains like biomedical literature mining and clinical text analysis. The complexity of these models, however, also poses significant challenges such as high computational costs, limited interpretability, domain shifts, factual unreliability, hallucination in generative systems, data privacy concerns, and ethical concerns in sensitive biomedical contexts. Thus, an extensive examination of deep learning-powered NLP should incorporate not only the architectures and technicalities but also the limitations of the models, their biomedical applicability, and responsible usage.

This review attempts to give a comprehensive academic overview about the natural language processing with deep learning, focusing on the key models, techniques, applications, challenges and future directions. Although NLP can be used in numerous applications in the world of artificial intelligence, in this article special attention will be paid to NLP's application in biomedical informatics, clinical text processing, digital health, biological knowledge extraction, and biomathematical research. It covers the evolution of NLP, the importance of deep learning architectures, the rise of the transformer models, the key NLP applications, biomedical and clinical applications of NLP, and the prospects of incorporating NLP knowledge into computational and mathematical models. The article demonstrates the increasing importance of deep learning-based NLP as a computational framework for future research in quantitative biology, healthcare analytics, and biomathematics, through the example of studying the biological and medical applications.

2. Evolution of Natural Language Processing

2.1 From Rule-Based Systems to Statistical NLP

Natural language processing (NLP) started with rule-based systems that used hand-coded linguistic rules, dictionaries, and patterns. These approaches were helpful for controlled language processing as they were transparent and traceable. But they were rigid and struggled with ambiguous, domain-specific and contextual language. In the biomedical and clinical domain, abbreviations, synonyms and domain-specific terms are common; this is especially true of biomedical and clinical text. Later, statistical NLP incorporated probabilistic and machine learning techniques to provide a way for systems to learn from text corpora. Methods such as the n-gram, hidden Markov models (HMMs), conditional random fields (CRFs) and traditional classifiers yielded better results in tasks such as text classification, part-of-speech tagging, and named entity recognition. But they still had to resort to feature engineering and lacked in semantic understanding.

2.2 Emergence of Deep Learning-Based NLP

Deep learning changed NLP by enabling models to learn linguistic features automatically from raw or minimally processed text. Whereas handcrafted features are exclusively relied upon by neural models, the former capture the semantic and contextual relationships between words. This transition enhanced the classification, sequence labeling, information extraction, summarization and language understanding of NLP systems.

In this time, neural architectures like convolutional neural networks, recurrent neural networks, long short-term memory networks, gated recurrent units, and encoder–decoder networks grew significant. These models worked well for sequence modelling and contextual analysis, especially in complex language tasks. They observed that deep learning-based language models have significantly enhanced the capabilities of natural language understanding, enabling multitask learning and shared representations between NLP tasks (Samant et al., 2022). Table 1 highlights the evolution of NLP, from rules-based systems designed manually to large-scale transformer and language models.

Table 1. Major stages in the evolution of natural language processing

Stage	Main Features	Key Limitation	Relevance
Rule-based NLP	Handcrafted rules, dictionaries, grammar patterns	Poor scalability	Useful for controlled terminology extraction

Statistical NLP	Probabilistic models and corpus-based learning	Limited semantic understanding	Supports early text classification and entity recognition
Machine learning NLP	Classifiers with engineered features	Requires manual feature design	Useful for supervised NLP tasks
Deep learning NLP	Neural representation learning	Requires larger data and computation	Improves classification, extraction, and sequence modeling
Transformer-based NLP	Self-attention and large-scale pretraining	High computational cost	Supports modern biomedical and clinical NLP
Large language models	General-purpose language understanding and generation	Risk of hallucination and bias	Useful for summarization, question answering, and knowledge extraction

2.3 Attention Mechanisms and Transformer Models

Recurrent models worked well on sequence processing but were not very good on long-range dependencies. To overcome this, attention mechanisms were developed to enable models to pay attention to the most relevant portion of the input text. This was a significant step toward transformer-based NLP, in which the key mechanism for learning contextual relationships between words was the self-attention.

Compared to strictly sequential processing, transformer models introduced self-attention to model longer text sequences more efficiently. This design allowed for extensive pre-training and fine-tuning, serving as the basis for numerous contemporary NLP applications. In recent years, transformer-based models have found extensive applications in text classification, question answering, summarization, information retrieval, text generation and biomedical text mining. Yenduri et al. (2024) noted that generative pretrained transformers have become crucial in the field of NLP, and Sharrab et al. (2025) pointed out that transformer models are increasingly being used in speech and language processing tasks. Figure 1 shows the conceptual evolution of NLP techniques from rule-based systems to LLM.

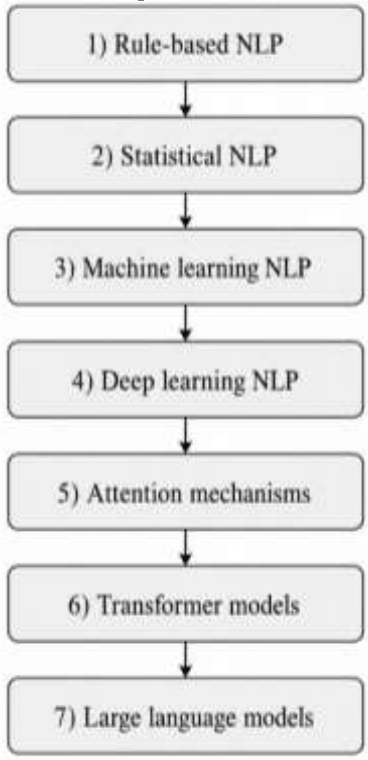

Figure 1: Evolution of NLP methods from rule-based systems to large language models.

2.4 Large Language Models and Current Directions

Large language models play an important role in the current state of NLP. They are trained on large amounts of text data and can be used for multiple tasks such as summarization, question answering, information extraction, text generation and dialogue. Their versatility has seen their use in scientific communication, clinical documentation, biomedical literature analysis, digital health, and decision-support systems.

But there are also significant challenges with large language models. They can produce misleading information, perpetuate bias, be difficult to understand, and be resource-intensive. In the biomedical and clinical settings, these are critical issues because accuracy, interpretability, privacy and human validation are required. As a result, recent NLP research has been focused on building trustworthy, interpretable, domain-specific, and safe language models for biomedical and biomathematical research.

3. NLP Deep Learning Models and Techniques

3.1 Text Representation and Embedding Techniques

Firstly, text representation is a crucial step in deep learning based NLP as raw text needs to be represented numerically for processing by neural models. Previous methods like one-hot encoding, bag-of-words, and TF-IDF encoded text as

sparse vectors, but were not very effective in capturing the semantics of the text. Deep learning also brought in dense word embeddings, which are continuous vector representations of words and enable models to capture the semantic similarity and context of words in a more effective way.
Contextual embeddings were also effective in enhancing the NLP domain, as it introduced a contextual meaning of words within the surrounding text. In biomedical and clinical language, abbreviations and technical terms can mean different things, depending on the context.

3.2 Neural Architectures for NLP
There are a number of neural architectures employed in deep learning based NLP. CNNs are able to identify local text patterns and are widely used in text classification. Recurrent neural networks are used to process sequential language data, but can be less effective with long-term dependencies. One such limitation is overcome by long short term memory networks and gated recurrent units which can retain important information across a long text span.
Encoder–decoder models are provided for use if one text sequence has to be transformed into another text sequence, like machine translation, summarization or question answering. In the attention-based models, the ability to focus attention on the relevant portions of the input text improves performance. In recent reviews, the capacity of NLP systems to learn complex linguistic representations has been greatly enhanced using deep learning architectures (Mienye & Swart, 2024; Younesi et al., 2024). Table 2 shows summary of major deep learning architectures in NLP, their main applications and popular NLP applications.

Table 2. Major deep learning architectures used in NLP

Architecture	Main Function	Common NLP Uses
CNN	Extracts local text features	Text classification
RNN	Processes sequential data	Language modeling
LSTM	Captures long-term dependencies	Named entity recognition
GRU	Efficient sequence modeling	Sequence classification
Encoder–decoder	Converts one sequence into another	Translation and summarization
Attention model	Focuses on relevant text	Question answering and extraction
Transformer	Learns contextual relationships	Modern NLP and text generation

3.3 Transformer Models and Large Language Models
The transformer model is now a key element of current NLP models, and is the most important since it is able to identify relationships between all the tokens in a text with the use of self-attention. This enables them to model higher-order dependencies than previous sequential models. Pre-trained transformer models can be used for specific tasks like classification, named entity recognition, relation extraction, summarization, and question answering and adapted to them.
The large language models are an extension of transformer-based NLP that allow more flexible language generation, conversations, summarising, extracting information, and answering questions. In the biomedical literature analysis, clinical documentation and biological knowledge extraction, these models are becoming more and more relevant. They also have some concerns regarding the hallucination, bias, interpretability and computational cost (Yenduri et al., 2024).

3.4 Training and Optimization Strategies
NLP training strategies are key to NLP performance. Labelled data: supervised learning, task specific data: pretraining and fine-tuning. Transfer learning is a method that allows a model to be trained on large amounts of data, then fine-tuned for a new task, such as biomedical and clinical NLP.
Multitask learning allows for multi-task learning to boost efficiency and generalisation. This is useful for NLP tasks such as classification, entity recognition, relation extraction, and question answering, which have similar linguistic characteristics. For improving natural language understanding via deep learning, Samant et al. emphasized the need for multitask learning.

4. The key applications of deep learning in NLP.
4.1 Core NLP Tasks
Text classification, NER, relation extraction, sentiment analysis, question answering, summarization, information retrieval, machine translation and text generation are some of the areas where deep learning based NLP techniques are widely used. The tasks enable models to classify documents, identify salient words, identify relationships, extract evidence, and provide natural language. These tasks have been made even better by transformer-based models and large language models that can understand long-range relationships and the meaning in text. Table 3, Major NLP tasks and their common applications, summarizes the major NLP tasks and their common applications.Table 3. Major NLP tasks and applications

NLP Task	Purpose	Common Applications
Text classification	Assigns categories to text	Document classification, clinical note labeling
Named entity recognition	Identifies important entities	Disease, drug, gene, protein, and symptom extraction
Relation extraction	Detects relationships between entities	Drug–drug, gene–disease, treatment–outcome relations
Sentiment analysis	Detects opinion or emotion	Patient feedback, vaccine hesitancy, mental health signals
Question answering	Generates answers from text	Biomedical and clinical decision support
Summarization	Produces concise summaries	Literature review, clinical note summarization
Information retrieval	Finds relevant documents	Biomedical search and evidence retrieval
Machine translation	Converts text across languages	Multilingual healthcare communication
Text generation	Produces new text	Report drafting, dialogue systems, documentation support

4.2 Biomedical and Clinical Applications

Biomedical and clinical NLP are major application areas of deep learning-based language processing. Biomedical literature, electronic health records, clinical notes, radiology reports, pathology reports, drug labels, and clinical trial records contain valuable information that is often stored as unstructured text. Deep learning-based NLP can extract diseases, symptoms, drugs, genes, proteins, procedures, adverse events, and treatment outcomes from these sources.

These applications support biomedical literature mining, disease classification, clinical decision support, pharmacovigilance, patient stratification, and medical report generation. Li et al. (2025) highlighted the role of deep learning in automatic radiology report generation, while Chen et al. (2026) discussed the use of AI in pharmaceutical administration and clinical pharmacy, including medication-related decision support. Figure 2 presents a general biomedical and clinical NLP workflow.

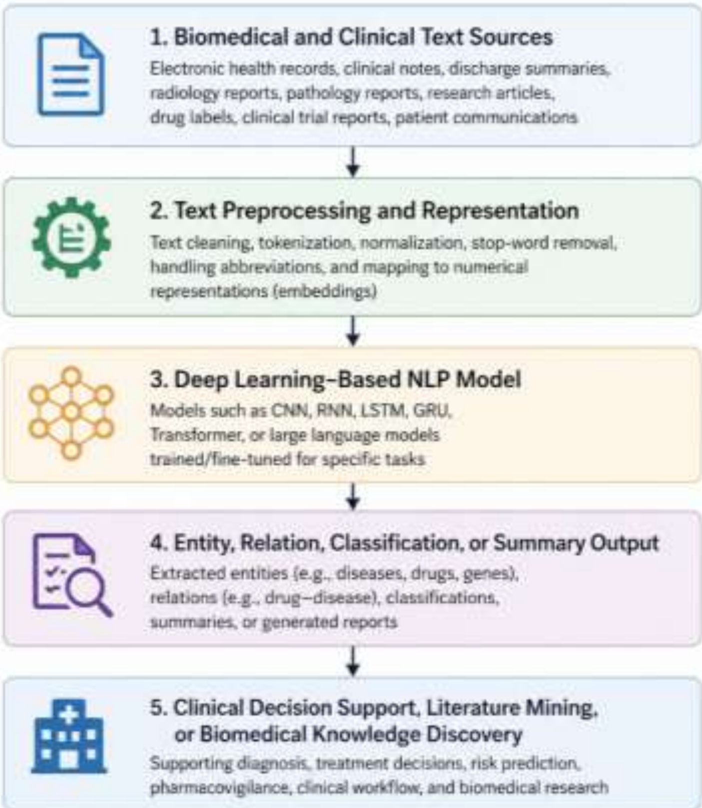

Figure 2. General workflow of deep learning-based NLP in biomedical and clinical applications

4.3 Digital Health and Public Health Applications

NLP technologies that leverage deep learning are increasingly applied in digital health and public health. Deep learning-based NLP can be applied to text data from remote monitoring devices, telehealth systems, mobile health apps, patient portals, social media and health discussion forums to detect symptoms, patient concerns, health opinions, fake news, and health trends. Shastry and Shastry (2023) outlined the use of deep learning and NLP in real-time remote monitoring for digital health.

Examples of public health uses include disease tracking, fake news detection, vaccine attitude and sentiment analysis, and mental health language. Sentiment analysis and fake news detection are particularly important for gauging public opinion during pandemics (Islam et al., 2024; Mridha et al., 2021). Recent studies on hate speech and psychological uses of large language models further demonstrate the potential applications of NLP in online safety and mental health (Albladi et al., 2025; Ke et al., 2025). Table 4 shows the major biomedical, clinical and public health applications of deep learning-based NLP.

Table 4. Application areas of deep learning-based NLP

Application Area	NLP Function	Example Use
Biomedical literature mining	Entity and relation extraction	Identifying disease, gene, drug, and pathway information
Electronic health records	Text classification and extraction	Detecting diagnoses, symptoms, and treatments
Radiology and pathology reports	Report generation and summarization	Supporting clinical documentation
Pharmacovigilance	Adverse event detection	Identifying drug safety signals
Clinical decision support	Question answering and information retrieval	Supporting diagnosis and treatment decisions
Digital health	Patient text analysis	Monitoring symptoms and patient communication
Public health surveillance	Classification and trend detection	Detecting disease signals and misinformation
Mental health analysis	Sentiment and language-pattern detection	Identifying emotional distress or risk signals

5. Relevance of NLP to Biomathematical Modeling

5.1 Extraction of Biological and Clinical Knowledge

Natural language processing is very important for biomathematical modelling since a lot of biological and medical knowledge is stored in an unstructured text form. Information about diseases, symptoms, genes, proteins, drugs, biological mechanisms, treatment responses and patient outcomes often appear in research articles, clinical notes, drug labels, trial reports, pathology reports, radiology reports, and public health documents. Using deep learning-based NLP, these entities and relationships can be captured and translated to structured information. This extraction process is crucial in biomathematical research as mathematical models frequently rely on precise variables, biological processes, and measurable relationships. Some examples include disease–gene association, drug–adverse event association, response to treatment patterns and biological pathway interaction. This helps to build up structured knowledge for the purposes of modelling biological and clinical systems.

5.2 Support for Mathematical and Computational Modeling

NLP can assist in mathematical/computational modelling by extracting the appropriate components of the model from biomedical literature and clinical data. Information from text can help to establish model parameters, to estimate the biological interactions, elucidate diseases mechanisms, and to search for reported values. These outputs can be used to inform disease progression, response to treatment, pharmacology, epidemiology and biological regulation modelling. From reports or digital text sources, NLP can be used to gather information regarding symptoms, outbreaks, transmission, intervention impacts, and public health responses in epidemiology. NLP can be used as a pharmacological modeling tool to help identify drug effects, adverse reactions, dosage information and treatment outcomes. In a systems biology context, NLP can help to capture biological interactions, which can be represented in the form of network models, ordinary differential equations, stochastic models or hybrid combinations of these. Ofori-Boateng et al. (2024) demonstrated that NLP, machine learning, and deep learning play an ever-growing role in formalizing the systematic review process in order to extract evidence from large volumes of literature. This is directly applicable to biomathematical modeling as systematic EEs can aid researchers in identifying model assumptions, biological variables, intervention effects, and reported quantitative relationships.

5.3 Integration with Knowledge Graphs and Predictive Models

Biomedical Knowledge Graphs and Predictive Models derived from Deep learning-based NLP can also help in biomathematical modeling. The knowledge graph is a network of entities and relationships that are structured, for example, the relationship between disease and gene, or the relationship between drug and target, or the relationship between symptom and disease, or the relationship between treatment and outcome. NLP can automatically identify these relationships from biomedical texts, and help to build or extend these graphs. Such knowledge graphs can then be applied in computational biology, clinical decision support, drug discovery and disease modelling. Some examples of disease–gene–drug networks can be used to uncover biological pathways, potential therapeutic targets, or links between molecular mechanisms and clinical outcomes. NLP can be used to derive knowledge, which can then be combined with predictive models to aid in the process of risk prediction, treatment stratification, hypothesis generation, and decision support. Table 5 outlines the relevance of NLP outputs to biomathematical modelling.

Table 5. NLP outputs and their relevance to biomathematical modeling

NLP Output	Example Extracted Information	Relevance to Biomathematical Modeling
Biomedical entities	Diseases, genes, proteins, drugs, symptoms	Defines variables and biological components

Clinical events	Diagnosis, treatment, relapse, recovery	Supports disease progression modeling
Entity relationships	Drug–disease, gene–disease, protein–protein relations	Supports network and pathway modeling
Quantitative information	Dosage, survival time, incidence, risk factors	Supports parameter estimation
Literature evidence	Study findings, reported outcomes, mechanisms	Supports model assumptions and validation
Public health text signals	Symptoms, outbreak reports, intervention responses	Supports epidemiological modeling
Knowledge graph links	Disease–gene–drug–pathway connections	Supports predictive and hybrid models

5.4 Role in Hybrid and Future Modeling Frameworks

Modern biomathematical research integrates mechanistic models with data-driven methods. NLP transforms textual biomedical evidence into structured inputs for models, e.g., biological interactions, clinical outcomes, and literature parameters. Valuable in fields like systems biology, pharmacometrics, epidemiology, digital health, and precision medicine. Helps bridge qualitative biomedical knowledge with quantitative models. Advances in deep learning-based NLP will enhance hybrid models combining theory, clinical data, literature mining, and computational predictions.

6. Challenges and Limitations

6.1 Technical Challenges

Domain shift: Models trained on general text struggle with biomedical/clinical text due to specialized language and abbreviations. Ambiguity and long-context handling remain difficult despite transformer advances. Robustness issues: Models sensitive to wording changes, noisy or incomplete data, and adversarial inputs.

6.2 Biomedical and Clinical Challenges

Sensitive patient data and privacy restrict access to large annotated datasets. Annotation requires expert knowledge and is costly. Clinical validation is critical before deployment to ensure accuracy, safety, and generalizability. Large language models risk generating fluent but incorrect outputs, necessitating evidence-grounded and expert-supervised systems.

6.3 Ethical and Reproducibility Challenges

Bias in training data can lead to unequal model performance across demographics and regions. Transparency and interpretability are needed for trust in clinical decisions. Reproducibility issues arise from differences in data preprocessing, model design, and evaluation. Responsible research requires clear reporting, code sharing, and thorough documentation of limitations.Table 6 summarizes the major challenges and limitations of deep learning-based NLP.

Table 6. Major challenges and limitations of deep learning-based NLP

Challenge Area	Main Issues	Relevance to Biomedical and Biomathematical Research
Domain shift	General models may fail on biomedical or clinical text	Limits transferability to specialized biological and medical domains
Ambiguity	Terms may have different meanings across contexts	Affects accuracy of disease, drug, and gene extraction
Noisy text	Clinical notes may contain abbreviations, errors, and incomplete sentences	Reduces reliability of clinical text analysis
Long-context processing	Important information may be spread across long documents	Affects literature mining and patient-record interpretation
Robustness	Models may be sensitive to wording changes or unexpected inputs	Limits real-world reliability
Privacy	Clinical text contains sensitive patient information	Restricts data access and model development
Hallucination	Generative models may produce unsupported claims	Creates risk in medical and scientific applications
Bias	Training data may reflect social or clinical inequalities	May reduce fairness across populations
Interpretability	Model decisions may be difficult to explain	Limits trust in clinical and scientific use
Reproducibility	Methods may be poorly documented or difficult to repeat	Weakens scientific reliability and comparison

7. Future Prospects

7.1 Explainable and Trustworthy NLP

The next generation of NLP systems should not only be more accurate, but also explainable, trustworthy and fact-based. This is especially important in biomedical and clinical applications where the model predictions could be used for diagnosis, treatment planning, patient monitoring or scientific analysis. Researchers should build explainable NLP models that can explain why they made a prediction, what evidence from the text was used and how uncertainty affects the results.

To be reliable, NLP models will need to become more fact-based to mitigate hallucinations in generative models and to increase confidence in clinical and scientific use.

7.2 Integration with Biomathematics and Computational Biology

One of the most important future directions is the integration of natural language processing and models from biomathematical and computational biology. NLP can be used to extract biological entities, clinical variables, disease mechanisms, intervention effects and parameter-related information from the literature and clinical documents. These outputs may support ordinary differential equation models, stochastic models, network models, epidemiological models, pharmacometric models, and systems biology frameworks.

This integration can help connect qualitative biomedical knowledge and quantitative modelling. For instance, disease–gene–drug relationships derived from NLP can help support biological network models, and epidemiological evidence derived from text can help improve disease transmission models. Future research should therefore develop hybrid systems that combine deep learning-based NLP with mathematical modeling, simulation and predictive analytics.

7.3 Domain-Specific and Multimodal Language Models

In the future, NLP models will be more domain-informed and multimodal. Future biomedical AI systems could be text-only or a combination of clinical notes, biomedical literature, medical images, omics data, sensor data, laboratory findings, and patient generated data. This direction is vital as biological and medical systems are complex and cannot be fully described through text alone.Furthermore, domain-informed language models should integrate biomedical ontologies, clinical guidelines, biological pathways, and medical knowledge bases. Such integration can enhance factual accuracy, interpretability, and relevance to biomedical research. Broader deep learning advancements in areas such as environmental modeling, EEG signal analysis and precision agriculture indicate a trend towards domain-specific deep learning, emphasizing the importance of domain-specific AI systems (Kumar et al., 2023; Raj et al., 2025; Upadhyay et al., 2025). Figure 3 Future integration of deep-learning-based NLP with biomedical data, mathematical modeling and decision support systems.

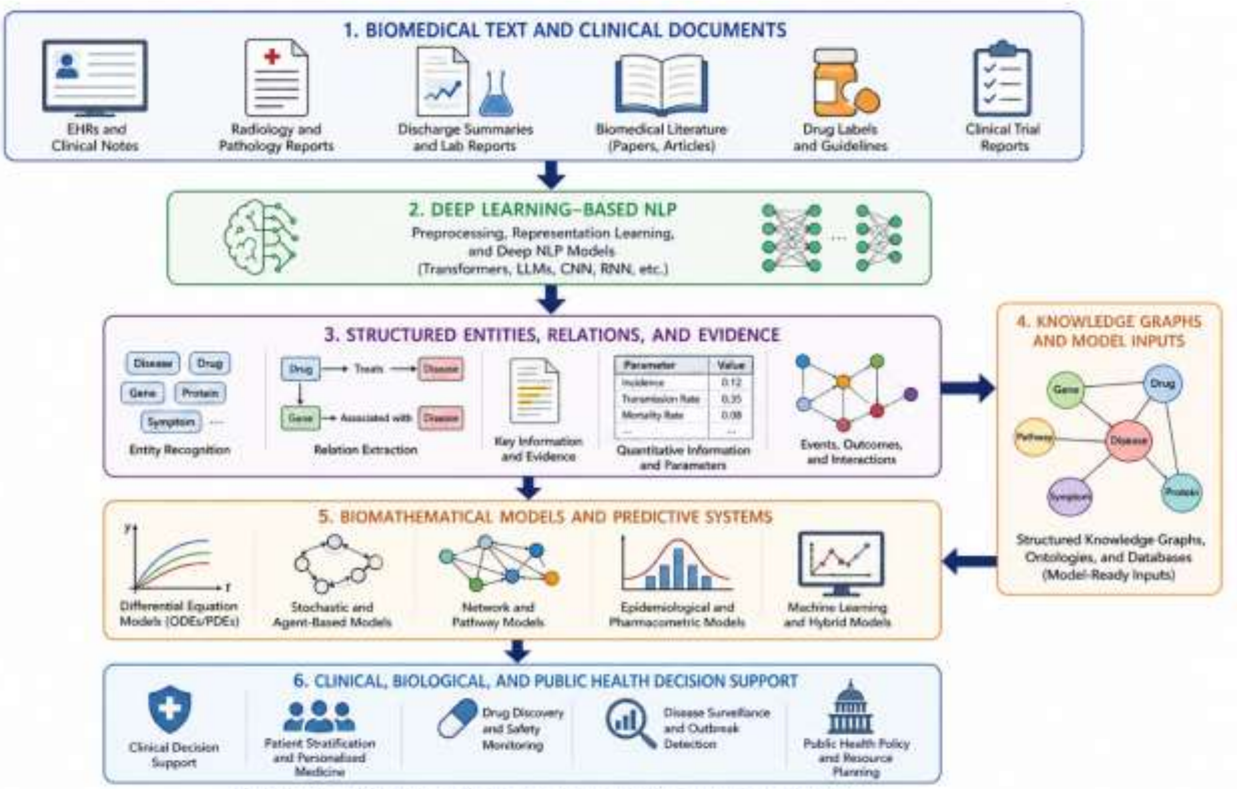

Figure 3. Future direction of NLP integration with biomedical data, mathematical modeling, and decision-support systems.

Figure 3. Future direction of NLP integration with biomathematical and biomedical systems

7.4 Multilingual, Public Health and Smart Healthcare Applications

Another major future direction is the development of multilingual and socially aware NLP systems. While many existing NLP models work best for English, biomedical and public health communication happens in many languages and cultural contexts. Sen et al. (2022) showed the importance of developing NLP resources and methods for languages like Bangla to highlight the larger need of inclusive and multilingual NLP research.

NLP will also become more and more important in smart healthcare and public health systems. Smart-city health platforms, telemedicine systems, digital surveillance networks, and public health communication systems generate large quantities of text that can be analyzed for disease trends, patient needs, misinformation, and emergency response. The work of Tyagi and Bhushan (2023) discussed the role of NLP in smart city applications which can be extended to health monitoring, public communication and urban public health decision making.

7.5 Deployment: Responsible and scalable

Future NLP systems should be responsibly deployed for real world biomedical and clinical use. This includes privacy-preserving learning, secure handling of patient data, regulatory compliance, bias monitoring and continuous performance evaluation. Federated learning and secure model sharing are among the techniques that may be critical to training NLP systems across healthcare organizations without direct patient data sharing.

Scalability is a big issue as well. Large language models are costly to compute and therefore difficult to deploy in low-resource clinical or research contexts. Future work should examine the development of efficient, lightweight and sustainable NLP models that can be adapted to different healthcare systems. Responsible deployment will require the collaboration of computer scientists, clinicians, mathematicians, biomedical researchers, ethicists, and policy makers. The major future directions of deep learning based NLP are listed in Table 7.

Table 7. Future directions of deep learning-based NLP

Future Direction	Main Focus	Relevance to Biomedical and Biomathematical Research
Trustworthy NLP	Explainability, uncertainty, factual grounding	Improves reliability in clinical and scientific use
NLP–biomathematics integration	Linking text-derived evidence with mathematical models	Supports disease modeling, systems biology, and simulation
Multimodal AI	Combining text with imaging, omics, EHRs, and sensor data	Enables more complete biomedical analysis
Domain-informed models	Incorporating ontologies, pathways, and medical knowledge	Improves biomedical accuracy and interpretability
Multilingual NLP	Supporting non-English biomedical and health text	Expands access and global health relevance
Public health NLP	Monitoring disease signals, misinformation, and health trends	Supports epidemiological surveillance and policy response
Privacy-preserving NLP	Secure learning and patient data protection	Enables ethical clinical deployment
Efficient deployment	Lightweight and sustainable models	Supports use in low-resource healthcare settings

In short, the future of deep learning-based NLP is to create systems that are more powerful, but also more interpretable, clinically reliable, mathematically useful, and ethically responsible. The most promising avenue for biomathematics is the fusion of knowledge from NLP with quantitative models that can enable biological discovery, disease prediction, treatment planning, and public health decision making.

8.CONCLUSION

Deep learning has transformed the field of natural language processing (NLP) by enabling models to learn intricate linguistic, semantic and contextual representations from large-scale textual data. In this review, we discussed the evolution of NLP from rule-based and statistical approaches to neural architectures, transformer models and large language models and their roles in text classification, named entity recognition, relation extraction, summarization, question answering, and text generation. Deep learning based NLP is also gaining more importance than general language processing in biomedical informatics, clinical documentation, electronic health record analysis, radiology reporting, pharmacovigilance, digital health and public health surveillance. This is particularly relevant to biomathematical research as it is able to extract structured entities, relationships, evidence and quantitative information from unstructured biomedical and clinical text. NLP-derived outputs can benefit knowledge graphs, disease networks, epidemiological models, pharmacological models, systems biology frameworks, and hybrid predictive systems combining textual evidence and mathematical and computational modeling. However, there are still several challenges including domain shift, data privacy, limitation of annotation, hallucination, bias, limited interpretability, computational cost and reproducibility . Future progress will require reliable, interpretable, domain-adapted, privacy-preserving, and clinically-validated NLP systems. In summary, deep learning based NLP should be viewed not only as a language technology, but also as a computational bridge that connects biomedical text, biological knowledge discovery, clinical decision support and quantitative biomathematical modeling.

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