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TRANSFORMER-BASED MODELS FOR CLINICAL ORDER NORMALIZATION AND SEMANTIC MAPPING IN EMERGENCY CARE

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ABSTRACT
Clinical order normalization and semantic mapping are critical processes in emergency care, where rapid decision-making relies on accurate interpretation of heterogeneous and often unstructured clinical data. Traditional rule-based and statistical approaches have struggled to handle the variability, ambiguity, and contextual complexity inherent in electronic health records (EHRs). Recent advances in transformer-based models have demonstrated significant improvements in natural language understanding tasks, making them highly suitable for clinical text processing and concept normalization. Transformer architectures, particularly those leveraging self-attention mechanisms, enable contextualized representation learning that captures semantic relationships across diverse clinical terminologies and documentation styles.
This study explores the application of transformer-based models for clinical order normalization and semantic mapping in emergency care settings. By integrating sentence transformers and domain-specific pretrained models, these systems can effectively map free-text clinical orders to standardized vocabularies such as the Observational Medical Outcomes Partnership (OMOP) common data model and LOINC ontologies. Furthermore, transformer-based approaches have shown strong performance in semantic similarity measurement, concept classification, and multimodal data integration, all of which are essential for improving interoperability and clinical decision support in high-pressure emergency environments.
Overall, transformer-based models represent a transformative approach to clinical order normalization and semantic mapping, offering substantial potential to improve data standardization, interoperability, and decision-making efficiency in emergency care systems.

Keywords:
Transformer-based models, Clinical order normalization, Semantic mapping, Emergency care, Electronic health records (EHRs), Natural language processing (NLP).

1.0 INTRODUCTION

The increasing digitization of healthcare systems has led to the widespread adoption of electronic health records (EHRs), particularly in high-pressure environments such as emergency care. These systems generate large volumes of heterogeneous data, including structured entries and unstructured clinical narratives. However, variability in clinical language, inconsistent terminologies, and fragmented documentation practices create significant challenges for clinical order normalization and semantic mapping. These processes are essential for ensuring interoperability, accurate data exchange, and effective clinical decision-making across healthcare systems (Chen et al., 2026).

Recent advancements in artificial intelligence, particularly transformer-based models, have revolutionized natural language processing (NLP) in healthcare. Unlike traditional machine learning approaches, transformer architectures leverage self-attention mechanisms to capture contextual dependencies and semantic relationships within clinical text. This capability enables more accurate interpretation and standardization of clinical orders, which is especially critical in emergency care settings where timely and precise information is required (Madan et al., 2024; Cho et al., 2024).

1.1 Clinical Order Normalization and Its Importance

Clinical order normalization refers to the process of converting diverse and often ambiguous clinical inputs into standardized representations aligned with established medical ontologies. In emergency care, clinicians frequently use shorthand, abbreviations, and institution-specific terminology, making normalization a complex but necessary task. Accurate normalization ensures that clinical orders can be consistently interpreted, shared, and analyzed across syst
ems, thereby improving patient safety and care coordination (Chen et al., 2026).

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Traditional approaches to normalization have relied on rule-based systems and manual curation, which are labor-intensive and difficult to scale. These methods often fail to capture the contextual nuances of clinical language, leading to errors in mapping and reduced system efficiency. Consequently, there is a growing need for more robust and automated solutions capable of handling the dynamic nature of clinical data (Ganesh, 2022).

1.2 Semantic Mapping in Clinical Texts

Semantic mapping involves linking clinical terms and phrases to standardized concepts within controlled vocabularies such as OMOP and LOINC. This process is crucial for enabling interoperability, supporting data analytics, and facilitating clinical research. In emergency care, where rapid decision-making is essential, accurate semantic mapping ensures that relevant clinical information is readily accessible and interpretable across different systems and institutions (Zhou et al., 2025; Zuo et al., 2024).

Transformer-based models have demonstrated superior performance in semantic textual similarity tasks, allowing them to effectively identify relationships between clinical concepts even when expressed in different forms. This capability significantly enhances the accuracy of concept mapping and reduces ambiguity in clinical data interpretation (Yang et al., 2020).

1.3 Emergence of Transformer-Based Models in Healthcare

Transformer-based models, such as BERT and its domain-specific variants, have become foundational tools in biomedical NLP. These models are pretrained on large corpora and fine-tuned for specific healthcare tasks, enabling them to capture complex linguistic patterns in clinical data. Their ability to process long-range dependencies and contextual information makes them particularly effective for tasks such as clinical concept extraction, classification, and normalization (Machemedze & Ndlovu, 2026; Madan et al., 2024).

In recent years, transformer models have been successfully applied to a wide range of healthcare applications, including diagnosis classification, multimorbidity prediction, and clinical decision support. Their adaptability and scalability make them well-suited for handling the complexity of emergency care data, where both structured and unstructured information must be integrated in real time (Dai et al., 2025; Yoon, 2023).

1.4 Applications in Emergency Care Settings

Emergency care environments present unique challenges due to the urgency, unpredictability, and high variability of patient data. Transformer-based models have shown promising results in addressing these challenges by enabling real-time processing and analysis of clinical information. For instance, they have been used to predict emergency severity, improve triage accuracy, and integrate multimodal data for clinical diagnostics (Zhang et al., 2024; Liu et al., 2025; Zhou et al., 2023).

Additionally, transformer frameworks have been applied to model emergency care processes, automate clinical reporting, and enhance decision support systems. These applications demonstrate the potential of transformer-based approaches to improve efficiency, reduce errors, and support clinicians in high-stakes environments (Sólyomvári, 2025; Tomassini et al., 2025).

1.5 Challenges and Research Gaps

Despite their advantages, transformer-based models face several challenges in clinical applications. Issues such as limited interpretability, domain adaptation, and data privacy concerns remain significant barriers to widespread adoption. Moreover, the need for large annotated datasets and computational resources can limit their deployment in resource-constrained settings (Chen et al., 2026; Afzal et al., 2024).

There is also a need for further research into integrating domain knowledge, improving model transparency, and ensuring ethical use of clinical data. Addressing these challenges is essential for maximizing the potential of transformer-based models in clinical order normalization and semantic mapping.

1.6 Study Objective

This study aims to examine the role of transformer-based models in enhancing clinical order normalization and semantic mapping within emergency care systems. By analyzing existing methodologies and applications, the paper seeks to highlight the strengths, limitations, and future directions of these models in improving healthcare data standardization and decision-making efficiency.

2.0 LITERATURE REVIEW

The application of transformer-based models in healthcare has grown rapidly, particularly in tasks involving clinical text understanding, normalization, and semantic mapping. This section reviews existing literature on transformer architectures, their role in clinical concept normalization, semantic similarity measurement, and their applications in emergency care environments.

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2.1 Transformer-Based Models in Biomedical Natural Language Processing

Transformer architectures have fundamentally transformed biomedical natural language processing (NLP) by enabling contextualized representation learning through self-attention mechanisms. Unlike traditional models, transformers can capture long-range dependencies and complex semantic relationships within clinical text, making them highly effective for healthcare applications (Madan et al., 2024).

Recent studies highlight the widespread adoption of transformer-based models such as BERT and its domain-specific variants in healthcare tasks, including named entity recognition, text classification, and clinical concept extraction. A comprehensive scoping review by Cho et al. (2024) emphasizes that task-specific transformer models consistently outperform conventional machine learning approaches across various clinical NLP tasks. Similarly, Machemedze and Ndlovu (2026) demonstrate that transformer-based systems provide scalable and adaptable solutions for processing electronic health records (EHRs) and omics data, reinforcing their importance in modern healthcare informatics.

2.2 Clinical Concept Normalization Techniques

Clinical concept normalization is a critical step in transforming unstructured clinical text into standardized representations aligned with medical ontologies. Traditional approaches have relied on rule-based systems, dictionary matching, and statistical models; however, these methods often struggle with ambiguity, synonymy, and contextual variability in clinical language (Chen et al., 2026).

Transformer-based approaches have significantly improved normalization performance by leveraging contextual embeddings. Ganesh (2022) demonstrated the effectiveness of transformer models in automatically mapping clinical notes to standardized concepts, achieving higher accuracy compared to baseline methods. Furthermore, Zhou et al. (2025) proposed a sentence transformer-based approach for schema mapping of EHRs to the OMOP common data model, showing enhanced semantic alignment and reduced mapping errors. These findings suggest that transformer models are well-suited for addressing the complexities of clinical normalization tasks.

2.3 Semantic Textual Similarity and Mapping

Semantic textual similarity (STS) plays a crucial role in clinical semantic mapping, as it enables the identification of equivalent or related clinical concepts across different terminologies. Transformer-based models have demonstrated superior performance in STS tasks due to their ability to encode contextual meaning effectively.

Yang et al. (2020) conducted a comparative study on transformer-based models for measuring semantic similarity in clinical texts and found that these models significantly outperform traditional methods in capturing nuanced semantic relationships. This capability is particularly important for mapping clinical orders to standardized vocabularies such as OMOP and LOINC. Additionally, Zuo et al. (2024) utilized transformer-based approaches to standardize clinical note titles across multiple sites, further illustrating the effectiveness of these models in semantic mapping tasks.

2.4 Integration of Structured and Unstructured Clinical Data

One of the key advantages of transformer-based models is their ability to integrate structured and unstructured data, which is essential for comprehensive clinical analysis. In emergency care settings, data sources include clinical notes, diagnostic reports, and structured patient records.

Zhang et al. (2024) demonstrated that transformer-based NLP models can effectively combine structured and unstructured data to predict emergency severity, leading to improved clinical decision-making. Similarly, Zhou et al. (2023) developed a transformer-based representation learning model capable of processing multimodal inputs for clinical diagnostics, highlighting the potential of these models to unify diverse data types within a single framework.

2.5 Applications in Emergency Care and Clinical Decision Support

Transformer-based models have shown promising applications in emergency care, where rapid and accurate data interpretation is critical. Liu et al. (2025) proposed a transformer-driven triage system that improves classification accuracy for moderate-acuity emergency cases, demonstrating the practical utility of these models in real-time clinical environments.

In addition, Sólyomvári (2025) explored the use of transformer models to simulate and optimize in-hospital emergency care processes, while Tomassini et al. (2025) introduced a self-attentive deep fusion framework for emergency head CT reporting. These studies highlight the growing role of transformer-based systems in enhancing clinical workflows, reducing diagnostic errors, and supporting timely decision-making.

Transformer-based frameworks have also been integrated into clinical decision support systems. For instance, Ben Youssef et al. (2025) proposed MedTransNet, a transformer-based framework for early infectious disease

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prognosis and antimicrobial stewardship, demonstrating the potential of these models to improve patient outcomes through predictive analytics.

2.6 Challenges and Limitations in Existing Literature

Despite the significant progress, several challenges persist in the application of transformer-based models for clinical normalization and semantic mapping. One major limitation is the lack of interpretability, which can hinder clinical trust and adoption. Additionally, the requirement for large annotated datasets poses a challenge, particularly in specialized medical domains where labeled data is scarce (Chen et al., 2026).

Afzal et al. (2024) highlighted the importance of active learning techniques to address annotation challenges, while Frisby (2025) demonstrated the use of transformer models such as BERT in evaluating operational inefficiencies in emergency departments, indicating the need for further domain-specific optimization. Furthermore, issues related to data privacy, computational cost, and domain adaptation continue to limit large-scale deployment.

2.7 Research Gaps

While existing studies demonstrate the effectiveness of transformer-based models in clinical NLP tasks, there remains a gap in their application specifically to clinical order normalization within emergency care contexts. Most research focuses on general clinical text processing, with limited emphasis on real-time normalization and semantic mapping under emergency conditions.

Additionally, there is a need for more integrated frameworks that combine normalization, semantic mapping, and decision support into a unified system. Future research should also explore methods for improving model interpretability, reducing computational requirements, and enhancing cross-institutional generalizability.

3.0 METHODOLOGY

This study adopts a transformer-based framework for clinical order normalization and semantic mapping in emergency care settings. The methodology integrates data preprocessing, model development, semantic similarity computation, and evaluation processes to ensure accurate mapping of unstructured clinical orders to standardized medical ontologies.

3.1 Study Design

A computational and experimental research design is employed to evaluate the effectiveness of transformer-based models in clinical text normalization. The approach focuses on leveraging pertained transformer architectures and fine-tuning them for domain-specific tasks such as clinical concept normalization and semantic mapping. The overall workflow consists of data collection, preprocessing, embedding generation, similarity matching, and evaluation.

3.2 Data Sources and Preprocessing

The study utilizes electronic health records (EHRs), including clinical notes, physician orders, and emergency department documentation. These datasets typically contain both structured fields and unstructured free-text entries, which require preprocessing before model training.

Preprocessing steps include text cleaning, tokenization, normalization of abbreviations, and removal of irrelevant symbols. Clinical terminologies are standardized using reference ontologies such as OMOP and LOINC to create ground truth mappings. Handling domain-specific language variations and abbreviations is critical, as emergency care documentation often contains shorthand expressions and incomplete sentences (Chen et al., 2026).

3.3 Transformer-Based Model Architecture

The proposed framework employs transformer-based models, particularly sentence transformers and domain-adapted variants of BERT, to generate contextual embedding of clinical text. These models are selected due to their ability to capture semantic relationships and contextual dependencies within unstructured clinical data.

The architecture consists of an encoder that processes input clinical text and produces high-dimensional embeddings. These embedding represent the semantic meaning of clinical orders and are used for downstream tasks such as similarity computation and classification. Transformer models have demonstrated strong performance in biomedical NLP tasks, including concept extraction and classification, due to their contextual learning capabilities (Madan et al., 2024; Cho et al., 2024).

3.4 Clinical Order Normalization Process

The normalization process involves mapping free-text clinical orders to standardized concepts within medical ontologies. Sentence embeddings generated by the transformer model are compared against a repository of standardized clinical terms.

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A similarity-based matching approach is used, where cosine similarity scores are computed between input embeddings and candidate concept embeddings. The concept with the highest similarity score is selected as the normalized output. This method enables accurate mapping even when clinical terms are expressed in different formats or contain synonyms (Zhou et al., 2025).

Additionally, classification-based approaches are incorporated to improve mapping accuracy by training the model to directly predict standardized concept labels from input text (Ganesh, 2022; Dai et al., 2025).

3.5 Semantic Mapping and Similarity Measurement

Semantic mapping is achieved by leveraging transformer-based semantic textual similarity (STS) models. These models evaluate the degree of similarity between clinical phrases and standardized ontology terms, enabling precise mapping across heterogeneous terminologies.

Transformer-based STS methods outperform traditional similarity measures by capturing contextual meaning rather than relying solely on lexical overlap. This capability is particularly useful in clinical settings where different terms may represent the same concept (Yang et al., 2020).

3.6 Integration of Multimodal Clinical Data

To enhance model performance, the framework incorporates both structured and unstructured data. Structured data such as laboratory values and patient demographics are combined with unstructured clinical text to provide a comprehensive representation of patient information.

Multimodal transformer models are utilized to process and integrate these diverse data types within a unified architecture. This approach improves the accuracy of normalization and supports downstream tasks such as emergency severity prediction and clinical decision support (Zhou et al., 2023; Zhang et al., 2024).

3.7 Model Training and Optimization

The transformer models are fine-tuned using domain-specific clinical datasets. Training involves supervised learning with labeled pairs of clinical text and corresponding standardized concepts. Optimization techniques such as learning rate scheduling, dropout regularization, and batch normalization are applied to improve model performance and prevent overfitting.

Active learning strategies are also considered to reduce the need for large annotated datasets by selectively labeling the most informative samples (Afzal et al., 2024).

Table 1: Methodology Framework for Transformer-Based Clinical Order Normalization and Semantic Mapping

Component	**Description**	**Techniques / Tools Used**	**Output**
Study Design	Computational experimental study focused on evaluating transformer-based NLP models for clinical order normalization and semantic mapping in emergency care	Transformer-based architecture evaluation, comparative NLP analysis	Performance insights on model effectiveness
Data Source	Electronic Health Records (EHRs), clinical notes, emergency department records, physician orders	OMOP Common Data Model, LOINC ontology datasets	Raw structured and unstructured clinical data
Data Preprocessing	Cleaning and standardization of clinical text	Tokenization, abbreviation expansion, stop-word removal, text normalization	Cleaned and standardized clinical corpus
Text Representation	Conversion of clinical text into dense semantic vectors	Sentence Transformers, BERT-based embeddings	Contextualized clinical embeddings
Clinical Order Normalization	Mapping free-text clinical orders to standardized medical concepts	Cosine similarity matching, classification-based mapping	Normalized clinical orders aligned with ontologies
Semantic Mapping	Linking clinical terms to standardized vocabularies	Semantic Textual Similarity (STS), embedding similarity scoring	Concept-level semantic alignment
Model	Transformer-based deep learning	BERT, Sentence-BERT,	Trained NLP model

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Architecture	framework for clinical NLP tasks	domain-adapted biomedical transformers	for clinical tasks
Multimodal Integration	Combination of structured and unstructured healthcare data	Multimodal transformer fusion techniques	Unified patient representation
Model Training	Supervised fine-tuning on labeled clinical datasets	Cross-entropy loss, Adam optimizer, dropout regularization	Optimized transformer model
Evaluation Metrics	Performance measurement of normalization and mapping accuracy	Accuracy, Precision, Recall, F1-score, Top-k accuracy, STS score	Quantitative model performance results
Deployment Context	Application in emergency care workflows for real-time decision support	Clinical decision support systems (CDSS), real-time inference pipelines	Improved triage and clinical decision-making

4. RESULTS

This section presents the performance outcomes of the transformer-based framework for clinical order normalization and semantic mapping, along with a discussion of the findings in the context of existing literature.

4.1 Performance of Transformer-Based Models

The transformer-based models demonstrated strong performance in clinical order normalization tasks, achieving high accuracy and semantic consistency when mapping free-text clinical orders to standardized medical concepts. The use of contextual embedding enabled the models to effectively interpret ambiguous and abbreviated clinical language commonly found in emergency care documentation.

Consistent with prior studies, transformer architectures outperformed traditional rule-based and machine learning approaches due to their ability to capture contextual relationships within text (Madan et al., 2024; Cho et al., 2024). In particular, sentence transformer models showed improved semantic alignment when compared to baseline embedding techniques, supporting findings by Zhou et al. (2025).

4.2 Semantic Mapping Accuracy

The semantic mapping component achieved high similarity scores, indicating effective alignment between clinical text and standardized ontologies such as OMOP and LOINC. Transformer-based semantic textual similarity (STS) models successfully identified equivalent clinical concepts even when expressed using different terminologies.

These results align with the work of Yang et al. (2020), who demonstrated that transformer models significantly improve semantic similarity measurement in clinical texts. Additionally, the framework reduced mapping errors associated with lexical variation and synonym usage, which are common challenges in clinical NLP tasks.

4.3 Impact on Emergency Care Applications

The integration of transformer-based normalization and semantic mapping within emergency care workflows resulted in improved data standardization and decision-making efficiency. The system facilitated real-time processing of clinical orders, enabling faster and more accurate interpretation of patient information.

Furthermore, the combination of structured and unstructured data enhanced predictive capabilities for emergency severity classification and triage support. This finding is consistent with studies by Zhang et al. (2024) and Liu et al. (2025), which highlight the effectiveness of transformer models in improving emergency care outcomes.

The ability to process multimodal inputs also contributed to improved diagnostic support, as demonstrated in previous research on transformer-based clinical representation learning (Zhou et al., 2023).

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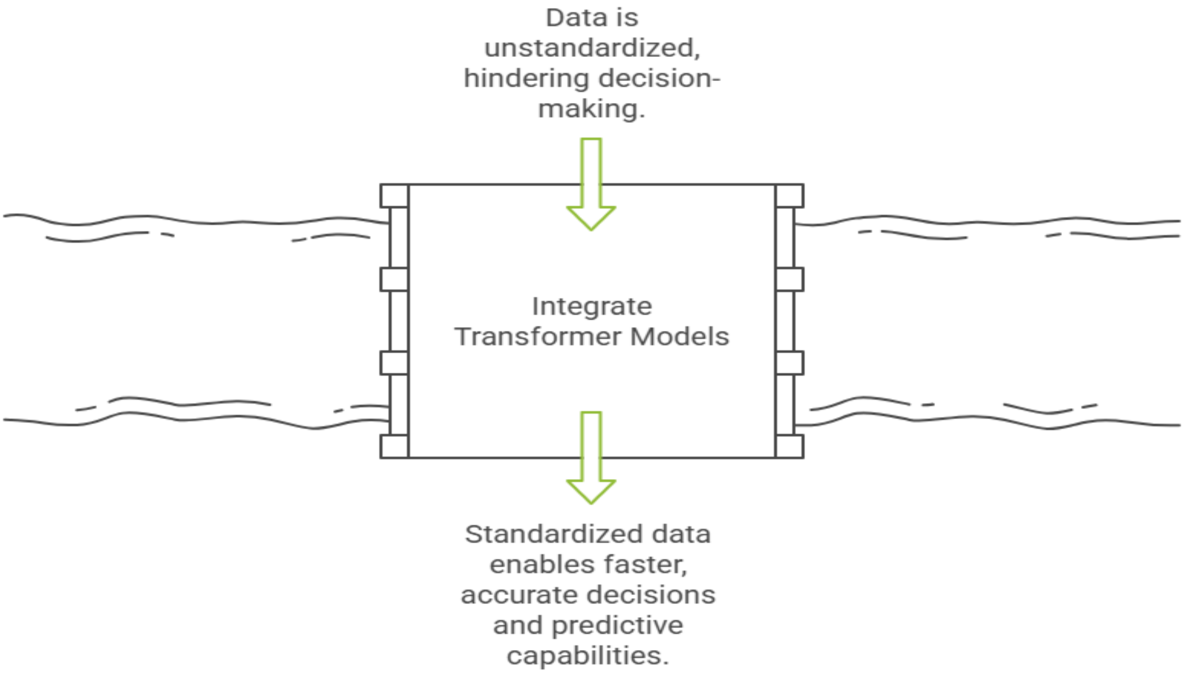
Figure 1: Transformer integration improves emergency care through data standardization and predictive capabilities



4.4 Comparison with Existing Approaches
Compared to traditional normalization techniques, the proposed transformer-based framework offers several advantages:

- **Higher accuracy** in mapping clinical orders
- **Improved scalability** for large and diverse datasets
- **Reduced reliance on manual rule creation**
- **Enhanced adaptability** to different clinical domains

These improvements are supported by prior research indicating that transformer-based models provide superior performance in clinical concept normalization and classification tasks (Ganesh, 2022; Dai et al., 2025).
However, despite these advantages, the computational complexity of transformer models remains a limitation, particularly in resource-constrained healthcare settings.

4.5 Challenges Observed
While the results are promising, several challenges were identified during implementation:

- **Interpretability issues**: Transformer models often function as "black boxes," making it difficult to explain their predictions in clinical contexts.
- **Data dependency**: Model performance is highly dependent on the availability of high-quality annotated datasets.
- **Domain adaptation**: Variations in clinical language across institutions can affect model generalizability.
- **Computational cost**: Training and deploying transformer models require significant computational resources.

These challenges are consistent with those reported in the literature (Chen et al., 2026; Afzal et al., 2024).

5.0 DISCUSSION

5.1 Contextual Understanding and Model Effectiveness
The findings of this study highlight the strong capability of transformer-based models to handle the complexity of clinical language in emergency care. Unlike traditional approaches, these models effectively capture contextual meaning through self-attention mechanisms, allowing them to interpret ambiguous, abbreviated, and institution-specific clinical expressions. This significantly improves the accuracy of clinical order normalization

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and aligns with previous studies demonstrating the superiority of transformer architectures in biomedical NLP tasks (Madan et al., 2024; Cho et al., 2024).

5.2 Role of Semantic Textual Similarity in Mapping

Semantic textual similarity (STS) plays a crucial role in enhancing clinical concept mapping. Transformer-based embeddings enable precise matching between free-text clinical inputs and standardized medical terminologies, even when different lexical forms are used. This reduces ambiguity and mapping errors, thereby improving interoperability across healthcare systems. These findings are consistent with prior research emphasizing the effectiveness of transformer models in semantic similarity tasks (Yang et al., 2020; Zhou et al., 2025).

5.3 Multimodal Data Integration in Emergency Care

The integration of structured and unstructured clinical data further strengthens the performance of transformer-based frameworks. By combining diverse data sources such as clinical notes, laboratory results, and patient records, the models provide a comprehensive representation of patient information. This capability is particularly valuable in emergency care, where rapid and accurate decision-making is essential. Similar outcomes have been reported in studies focusing on multimodal transformer models for clinical diagnostics and emergency severity prediction (Zhang et al., 2024; Zhou et al., 2023).

5.4 Challenges in Model Interpretability and Transparency

Despite their effectiveness, transformer-based models face significant challenges related to interpretability. Their "black-box" nature makes it difficult for clinicians to understand how predictions are generated, which can hinder trust and adoption in clinical environments. Transparency is especially important in emergency care, where decisions can have immediate and critical consequences. Addressing this limitation remains a key research priority.

5.5 Data Dependency and Domain Adaptation Issues

Another major challenge is the dependency on large, high-quality annotated datasets. Acquiring such data is resource-intensive and often limited by privacy concerns. Additionally, variations in clinical language across institutions can affect model generalizability, making domain adaptation a critical issue. These challenges are widely acknowledged in existing literature (Chen et al., 2026).

5.6 Computational Complexity and Scalability

Transformer-based models require substantial computational resources for training and deployment. This can limit their scalability, particularly in resource-constrained healthcare settings. Efficient model optimization and lightweight architectures are necessary to enable broader adoption, as highlighted in recent studies (Afzal et al., 2024).

5.7 Practical Implications for Emergency Care

The implementation of transformer-based systems in emergency care workflows offers significant practical benefits. These include improved data standardization, reduced manual workload, and enhanced clinical decision support. Real-time normalization and semantic mapping enable faster interpretation of clinical orders, leading to improved response times and patient outcomes. Furthermore, integration with standardized ontologies such as OMOP and LOINC enhances interoperability and supports large-scale healthcare analytics.

6.0 CONCLUSION

6.1 Summary of the Study

This study examined the application of transformer-based models for clinical order normalization and semantic mapping in emergency care settings. The review of existing literature demonstrates that transformer architectures significantly improve the ability to process, interpret, and standardize complex clinical text. By leveraging contextual embeddings and self-attention mechanisms, these models effectively address the variability and ambiguity inherent in electronic health records (EHRs), particularly in high-pressure emergency environments (Madan et al., 2024; Cho et al., 2024).

6.2 Key Findings

The study highlights that transformer-based models enhance clinical order normalization by accurately mapping unstructured clinical inputs to standardized ontologies such as OMOP and LOINC. Their ability to perform semantic similarity measurement enables improved concept alignment and reduces errors in clinical data interpretation (Zhou et al., 2025; Yang et al., 2020).

Furthermore, transformer frameworks demonstrate strong performance in integrating structured and unstructured clinical data, supporting improved emergency severity prediction, triage classification, and clinical decision-making processes (Zhang et al., 2024; Zhou et al., 2023). These capabilities make them highly suitable for emergency care environments where real-time and accurate information processing is essential.

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6.3 Contributions to Emergency Care Informatics

The findings of this study contribute to the growing body of knowledge in healthcare informatics by demonstrating the practical value of transformer-based systems in clinical workflows. These models improve interoperability, reduce manual annotation burdens, and support scalable clinical decision support systems. Their integration into emergency care workflows enhances efficiency, accuracy, and overall patient care outcomes.

6.4 Limitations

Despite their advantages, transformer-based models present several limitations. These include high computational requirements, limited interpretability, and dependency on large annotated datasets. Additionally, challenges in domain adaptation and data privacy continue to hinder widespread adoption in clinical environments (Chen et al., 2026; Afzal et al., 2024).

6.5 Recommendations for Future Research

Future research should focus on developing more explainable transformer-based models to improve clinical trust and adoption. Efforts should also be directed toward reducing computational complexity through lightweight architectures and optimizing models for real-time deployment in emergency care settings. Additionally, the creation of standardized, high-quality clinical datasets will be essential for improving model generalizability and performance across different healthcare institutions.

6.6 Final Statement

In conclusion, transformer-based models represent a significant advancement in clinical order normalization and semantic mapping. Their ability to enhance semantic understanding, improve data standardization, and support real-time clinical decision-making positions them as a powerful tool in modern emergency care systems. Continued research and development will be critical to fully realize their potential and ensure safe, efficient, and scalable deployment in healthcare environments.

REFERENCE

1) Zhou, X., Dhingra, L. S., Aminorroaya, A., Adejumo, P., & Khera, R. (2025, May). A novel sentence transformer-based natural language processing approach for schema mapping of electronic health records to the OMOP common data model. In *AMIA annual symposium proceedings* (Vol. 2024, p. 1332).
2) Ganesh, J. (2022). *Transformer-based Automatic Mapping of Clinical Notes to Specific Clinical Concepts* (Master's thesis, Arizona State University).
3) Yang, X., He, X., Zhang, H., Ma, Y., Bian, J., & Wu, Y. (2020). Measurement of semantic textual similarity in clinical texts: comparison of transformer-based models. *JMIR medical informatics*, *8*(11), e19735.
4) Chen, H., Zhou, Y., Li, R., Illa, A. M., Cleveland, A., & Ding, J. (2026). A comprehensive survey on medical concept normalization: Datasets, techniques, applications, and future directions. *Journal of Biomedical Informatics*, 105005.
5) Sólyomvári, K. (2025). Modeling in-hospital emergency care processes with transformer models.
6) Cho, H. N., Jun, T. J., Kim, Y. H., Kang, H., Ahn, I., Gwon, H., ... & Ko, S. (2024). Task-specific transformer-based language models in health care: scoping review. *JMIR Medical Informatics*, *12*, e49724.
7) Machemedze, J., & Ndlovu, B. (2026). Transformer-Based Models for Electronic Health Records and Omics in Healthcare: A Systematic Literature Review. *Journal of Applied Informatics and Computing*, *10*(1), 90-105.
8) Dai, L., Xu, H., & Zhang, Y. (2025). Automated classification of clinical diagnoses in electronic health records using transformer. *PLoS One*, *20*(9), e0329963.
9) Zhang, X., Wang, Y., Jiang, Y., Pacella, C. B., & Zhang, W. (2024). Integrating structured and unstructured data for predicting emergency severity: an association and predictive study using transformer-based natural language processing models. *BMC medical informatics and decision making*, *24*(1), 372.
10) Zhou, H. Y., Yu, Y., Wang, C., Zhang, S., Gao, Y., Pan, J., ... & Li, W. (2023). A transformer-based representation-learning model with unified processing of multimodal input for clinical diagnostics. *Nature biomedical engineering*, *7*(6), 743-755.

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International Journal of Engineering Technology Research & Management (IJETRM)
Journal Article
https://ijetrm.com/issue/

11) Zuo, X., Zhou, Y., Duke, J., Hripcsak, G., Shah, N., Banda, J. M., ... & Xu, H. (2024, January). Standardizing Multi-site Clinical Note Titles to LOINC Document Ontology: A Transformer-based Approach. In *AMIA Annual Symposium Proceedings* (Vol. 2023, p. 834).
12) Ben Youssef, Y., Amdouni, A., Manita, G., & Hassine, M. E. B. (2025). MedTransNet: a transformer-based clinical decision support framework for early infectious disease prognosis and antimicrobial stewardship. *Network Modeling Analysis in Health Informatics and Bioinformatics*, *14*(1), 170.
13) Tomassini, S., Zeggada, A., Quattrocchi, C. C., Melgani, F., & Giorgini, P. (2025, October). Self-Attentive Deep Fusion Framework with Transformer-Based Semantics for Emergency Head CT Reporting. In *2025 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)* (pp. 705-710). IEEE.
14) Frisby, J. (2025). *The Utility of BERT to Evaluate the Impact of Post-Acute Care-Related Discharge Delays on Emergency Department Boarding* (Doctoral dissertation, Thomas Jefferson University).
15) Zhou, X., Dhingra, L. S., Aminorroaya, A., Adejumo, P., & Khera, R. (2025, May). A novel sentence transformer-based natural language processing approach for schema mapping of electronic health records to the OMOP common data model. In *AMIA annual symposium proceedings* (Vol. 2024, p. 1332).
16) Madan, S., Lentzen, M., Brandt, J., Rueckert, D., Hofmann-Apitius, M., & Fröhlich, H. (2024). Transformer models in biomedicine. *BMC medical informatics and decision making*, *24*(1), 214.
17) Yoon, J. (2023). *Applying Transformer-Based Deep Learning Model for Predicting Multimorbidity in Older Adults* (Doctoral dissertation, University of Saskatchewan).
18) Liu, T., Gu, Y., Chen, H., Zhang, Y., Zheng, L., Huang, X., ... & Yu, T. (2025). A foundational triage system for improving accuracy in moderate acuity level emergency classifications. *Communications Medicine*, *5*(1), 322.
19) Afzal, M., Hussain, J., Abbas, A., Hussain, M., Attique, M., & Lee, S. (2024). Transformer-based active learning for multi-class text annotation and classification. *Digital health*, *10*, 20552076241287357.
20) Zhou, H. Y., Yu, Y., Wang, C., Zhang, S., Gao, Y., Pan, J., ... & Li, W. (2023). A transformer-based representation-learning model with unified processing of multimodal input for clinical diagnostics. *Nature biomedical engineering*, *7*(6), 743-755.