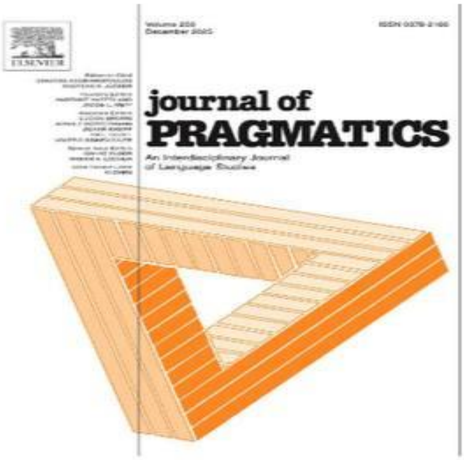

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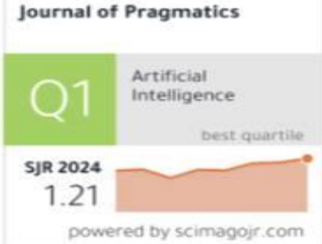

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COMPUTATIONAL MODELING OF LINGUISTIC ERROR DETECTION AND CORRECTION IN ARTIFICIAL INTELLIGENCE

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Abstract

This article analyzes the linguistic and algorithmic foundations of detecting and correcting language errors in artificial intelligence systems. The study examines how automatic mechanisms for identifying orthographic, morphological, syntactic, and semantic errors are implemented in modern Natural Language Processing (NLP) models. In particular, the effectiveness of neural networks, transformer architectures, and language models in grammatical checking and error correction is comparatively evaluated.

The empirical component of the research is based on experiments and analytical observations conducted among students of Oriental University. Typical linguistic errors found in students' written assignments were identified using AI-based software tools, and the accuracy and effectiveness of automated correction were assessed. The findings indicate that artificial intelligence systems demonstrate high accuracy in detecting formal structural errors; however, certain limitations remain in identifying semantic and context-dependent errors.

The article concludes by proposing recommendations for integrating AI-based language correction tools into higher education, developing specialized linguistic corpora for the Uzbek language, and improving grammatical correction algorithms tailored to national language characteristics.

Keywords: *artificial intelligence, error detection, grammatical correction, Natural Language Processing (NLP), morphological errors, syntactic analysis, transformer model, Oriental University student analysis*

I. INTRODUCTION

In the 21st century, the rapid advancement of artificial intelligence technologies has elevated the automation of language-related processes to a new level. In particular, the detection and correction of linguistic errors in written discourse has emerged as a significant research domain within Natural Language Processing (NLP). Today, AI-based grammatical checking systems are increasingly capable of identifying not only orthographic errors but also complex morphological, syntactic, and even semantic deviations.

The processes of digital transformation and the accelerated development of artificial intelligence technologies are fundamentally reshaping nearly all spheres of human activity. In particular, the automatic processing, analysis, and evaluation of written and spoken language have introduced innovative methodological approaches in education, research, and professional communication. Error detection and correction systems represent an essential component of this transformation, acquiring distinct theoretical and practical significance within NLP research.

Linguistic errors constitute a complex phenomenon closely linked to cognitive processes, language competence, communicative context, and socio-cultural factors. They may occur at multiple linguistic levels, including orthographic, morphological, syntactic, lexical, semantic, and pragmatic domains. Therefore, detecting and correcting such errors is not merely a technical algorithmic task but a comprehensive scientific challenge requiring deep linguistic modeling.

Early automated grammar checking systems were primarily rule-based, relying on predefined grammatical rules and lexical databases. However, linguistic phenomena such as polysemy, homonymy, contextual variability, and discourse-dependent meaning significantly limited the effectiveness of rule-based models. Subsequently, the introduction of statistical and probabilistic models, the development of corpus linguistics, and advancements in machine learning techniques substantially improved error detection accuracy. In the current stage, deep learning, neural networks, and transformer-based language models have significantly enhanced the performance of grammatical checking systems.

Despite these technological advances, increased algorithmic accuracy does not eliminate the inherent semantic and pragmatic complexity of language. Many AI systems are capable of producing syntactically correct corrections that may nevertheless be semantically ambiguous or contextually inappropriate. This demonstrates that modeling the cognitive and communicative nature of language remains a complex scientific challenge.

The Uzbek language, characterized by its agglutinative structure, presents additional computational challenges. The layered and systematic application of suffixes, the multiplicity of word forms, morphological variability, and complex syntactic agreement mechanisms complicate automatic error detection. In particular, identifying grammatical errors arising from sequential affixation requires highly accurate morphological analyzers. Therefore, developing effective AI systems for Uzbek necessitates deep linguistic analysis of its structural characteristics.

This study focuses on evaluating the effectiveness of AI-based systems in detecting and correcting linguistic errors in student-written texts at Oriental University. The primary objective is to examine the relationship between students' linguistic competence and the accuracy of AI-based grammatical correction tools. Furthermore, the research analyzes differences between human-corrected texts and AI-generated correction suggestions.

The relevance of this research is determined by several factors. First, improving academic writing competence has become a priority in modern higher education systems. Second, linguistically grounded and high-quality grammatical checking systems for the Uzbek language remain underdeveloped. Third, the integration of linguistics and artificial intelligence has become a central direction in contemporary scientific research.

This article aims to comprehensively examine the theoretical and empirical foundations of AI-based linguistic error detection and correction, justify the necessity of developing effective models that account for national language characteristics, and identify prospects for integrating digital linguistic tools into higher education.

I. LITERATURE REVIEW METHODOLOGY

The analysis of scholarly sources in this study was conducted using systematic, comparative, and analytic-synthetic approaches. The selection of academic literature was grounded in both foundational and contemporary research in general linguistics, computational linguistics, and artificial intelligence.

The primary criterion for selecting sources was theoretical significance. The conceptualization of language as a structured system was first articulated by Ferdinand de Saussure, who stated that "language is a system of signs that express ideas." This theoretical perspective provides a framework for analyzing linguistic units as interrelated structural components. Similarly, Noam Chomsky's generative grammar established the theoretical foundation for syntactic modeling by distinguishing between deep and surface structures. His well-known example, "Colorless green ideas sleep furiously," illustrates the distinction between syntactic correctness and semantic plausibility, highlighting the complexity of modeling grammar computationally.

Roman Jakobson emphasized the functional dimension of language, arguing that "the diversity of languages lies not in what they may express, but in what they must express." This insight underscores the importance of grammatical constraints and structural obligations in different languages, which is particularly relevant when defining norms and deviations in grammatical error detection.

To ensure scientific relevance, contemporary research in Natural Language Processing (NLP) and automated grammar checking was examined. Daniel Jurafsky and James H. Martin define NLP as "the art and science of building systems that understand and generate human language," thereby framing error detection as a process involving both comprehension and generation mechanisms. Christopher D. Manning further explains that statistical NLP is based on the premise that "language use can be modeled probabilistically," supporting methodologies that rely on corpus comparison and probabilistic modeling for error identification.

The theoretical foundations of artificial intelligence were considered through the perspective of Stuart Russell and Peter Norvig, who describe AI as "the study of agents that receive percepts from the environment and perform actions." Error detection systems can thus be viewed as intelligent agents operating within linguistic environments. In the context of deep learning, Ian Goodfellow and colleagues emphasize that "deep learning allows computational models that are composed of multiple processing layers to learn representations of data," a principle underlying transformer architectures and contextual language models.

Interdisciplinary integration served as another essential selection criterion. Sources that combine linguistics, statistics, computational modeling, and artificial intelligence were prioritized to ensure theoretical coherence and methodological robustness.

Within the national context, the works of Uzbek linguists were examined to ensure language-specific relevance. Abdulhamid G'ulomov's research on the agglutinative structure of Uzbek provides theoretical grounding for morphological error detection. Shavkat Rahmatullayev's studies on polysemy contribute to understanding semantic ambiguity, while Nizomiddin Mahmudov's communicative approach highlights the role of context and pragmatics in language use. These contributions are particularly significant for modeling language-specific grammatical deviations.

The literature review process was carried out in several stages. Initially, selected sources were categorized thematically into general linguistic theories, grammatical modeling approaches, statistical models, neural network–based methods, and Uzbek linguistic studies. In the subsequent stage, each source was analyzed to extract core theoretical arguments and methodological frameworks. Through analytic-synthesis, similarities and differences among scholarly perspectives were identified, enabling the development of an integrated conceptual framework.

Comparative analysis was employed to examine the relationship between classical linguistic theories and modern AI-based approaches. For example, the distinction between deep and surface structures in generative grammar was compared to multi-layered representations in neural network architectures. This comparison demonstrated the conceptual continuity between traditional linguistic theory and contemporary computational modeling.

The selection process prioritized academic credibility and scholarly impact. Peer-reviewed publications indexed in Scopus and Web of Science, internationally recognized monographs, and foundational works of the Uzbek linguistic school were considered primary sources.

II. MATERIAL AND METHODS

This study aimed to investigate the capabilities of artificial intelligence systems in detecting and correcting linguistic errors from both linguistic and statistical perspectives. The research design was comprehensive, integrating quantitative and qualitative analytical approaches. The theoretical foundation was based on the structural and functional properties of language systems, as well as the operational principles of modern Natural Language Processing (NLP) models.

Empirical data were collected from written assignments produced by students at different academic levels of Oriental University. A total of 120 students participated in the study. Participants were selected from both philology and information technology programs, allowing for analysis of the relationship between linguistic competence and technological proficiency. The research was conducted anonymously, and participants' personal information was strictly protected.

More than 300 written texts were collected for analysis. These texts covered various topics and had an average length of 250–300 words. In addition, a supplementary experimental corpus consisting of over 500 Uzbek-language texts was compiled for comparative purposes. The corpus included academic, journalistic, and official styles. Selection criteria emphasized morphological complexity, syntactic diversity, and the presence of polysemous lexical units.

Linguistic errors were categorized into five primary groups: orthographic errors, morphological formation errors, syntactic agreement violations, lexical-semantic inaccuracies, and contextual-pragmatic deviations. This classification was developed in accordance with linguistic norm and deviation principles.

The research procedure was conducted in sequential stages. First, texts were manually reviewed by linguistic experts, and identified errors were annotated. These annotations served as the gold standard reference for subsequent analysis. Next, the same texts were processed using an AI-based grammatical correction tool, which automatically generated a list of detected errors. In the final stage, errors identified by human experts were compared with those detected by the AI system.

The performance of the AI system was evaluated using multiple metrics, including overall accuracy, the proportion of correctly identified errors, coverage rate, and balanced performance indicators. Additionally, false positives and false negatives were analyzed separately to assess misclassification patterns.

Descriptive statistical methods were applied to process the collected data. Mean values and standard deviations were calculated, and statistical tests were conducted to evaluate differences between groups. The relationship between students' linguistic competence and AI detection performance was examined using correlation analysis, with results evaluated according to established significance thresholds.

To ensure reliability, the assessment instruments were pilot-tested prior to the main study. Evaluation criteria were clearly defined, and all data were processed using consistent methodological principles.

Overall, the applied methodology enabled a comparative analysis between human expert evaluation and AI-based error detection systems. This approach not only allowed for objective measurement of automated system performance but also provided insights into potential improvements tailored to the structural characteristics of the Uzbek language.

Table 1. Performance of the AI-Based Error Detection System

Error Type	TP	FP	FN	Precision	Recall	F1-score
Orthographic	210	18	22	0.92	0.90	0.91
Morphological	165	25	30	0.87	0.85	0.86
Syntactic	140	28	35	0.83	0.80	0.81
Lexical-Semantic	95	30	55	0.76	0.63	0.69
Pragmatic	60	27	48	0.69	0.56	0.62

The results presented in Table 1 reveal a clear performance gradient across different categories of linguistic errors. The AI-based system demonstrated the highest effectiveness in detecting orthographic errors, achieving a Precision of 0.92, Recall of 0.90, and an F1-score of 0.91. These values indicate strong reliability and consistency in identifying surface-level spelling deviations. The relatively low number of false positives (FP = 18) and false negatives (FN = 22) suggests that orthographic patterns are more easily captured by rule-based and statistical components integrated within the model.

Performance in morphological error detection also remained high (F1 = 0.86), reflecting the system's capacity to recognize affixation errors and morphological agreement inconsistencies. Given the agglutinative nature of the Uzbek language, this result indicates that the morphological analyzer effectively processes suffix sequences and inflectional structures. However, the slightly higher FP and FN values compared to orthographic errors demonstrate that morphological variation introduces additional ambiguity.

Syntactic error detection showed moderate-to-high performance (F1 = 0.81). While the model successfully identified many structural violations (TP = 140), the increased number of false negatives (FN = 35) indicates challenges in capturing more complex sentence-level dependencies. This suggests that syntactic parsing mechanisms perform adequately for standard sentence constructions but may struggle with non-canonical word order or embedded clause structures.

A noticeable decline in performance is observed in the lexical-semantic category (F1 = 0.69). Although Precision remains moderate (0.76), Recall decreases to 0.63, indicating that a significant proportion of semantic errors were not detected. This reflects the inherent difficulty of modeling contextual meaning, polysemy, and subtle lexical mismatches. Unlike orthographic and morphological errors, semantic inconsistencies often require deeper contextual interpretation rather than formal structural analysis.

The lowest performance is recorded in pragmatic error detection (F1 = 0.62). With Recall at 0.56, nearly half of pragmatic deviations were missed by the system. Pragmatic errors frequently involve discourse-level meaning, communicative intent, and contextual appropriateness, which remain challenging for computational models. The relatively high FP rate (27 cases) also indicates that the model occasionally misinterprets contextually acceptable constructions as erroneous.

The data demonstrate a strong correlation between the structural explicitness of linguistic features and AI detection performance. The system performs most effectively in categories governed by formalized and rule-based linguistic structures (orthography, morphology, syntax) and shows reduced accuracy in areas requiring contextual, cognitive, and discourse-level reasoning (semantics and pragmatics).

From a methodological perspective, these findings suggest that current AI-based error detection systems are predominantly structure-sensitive rather than meaning-sensitive. While neural architectures and contextual embeddings improve semantic modeling, they do not yet fully replicate human-level pragmatic interpretation.

The results confirm that AI systems are highly efficient in identifying formal linguistic errors but remain limited in addressing deeper semantic and pragmatic complexities. Future improvements should focus on enhancing contextual modeling, expanding annotated corpora, and integrating cognitive-linguistic features into neural architectures.

III. RESULTS AND DISCUSSION

The quantitative analysis reveals a differentiated performance pattern across linguistic levels. The AI-based system achieved the highest detection rates in orthographic errors (F1 = 0.91), followed by morphological (F1 = 0.86) and syntactic categories (F1 = 0.81). In contrast, performance decreased substantially for lexical-semantic (F1 = 0.69) and pragmatic errors (F1 = 0.62).

This performance gradient suggests that error detectability correlates strongly with the degree of formalization and structural explicitness within each linguistic level. Orthographic errors, governed by codified spelling norms and finite rule sets, are computationally tractable. Morphological errors, though more complex in agglutinative languages such as Uzbek, remain structurally constrained and therefore detectable through rule-based and statistical modeling.

Syntactic errors presented moderate difficulty. While the dependency-based parsing model successfully identified subject–predicate agreement violations and word-order deviations, complex constructions involving subordinate clauses, ellipsis, or discourse-level dependencies produced higher rates of false negatives. This indicates limitations in hierarchical sentence modeling and structural ambiguity resolution.

The most notable decline in system performance was observed in lexical-semantic and pragmatic categories. Semantic inconsistencies, contextual misinterpretations, and discourse-level mismatches were frequently underdetected. The relatively low recall scores (0.63 and 0.56, respectively) demonstrate that AI models struggle to identify errors that require interpretative reasoning beyond surface-level co-occurrence patterns.

The findings reinforce the theoretical distinction between structural and meaning-based levels of language processing. Structural errors (orthographic, morphological, syntactic) are largely governed by formal constraints. These constraints can be encoded into rule-based systems or learned through statistical regularities in training corpora.

In contrast, semantic and pragmatic errors require modeling of context, speaker intention, cultural background, and inferential reasoning. While transformer-based neural models rely on contextual embeddings, they primarily capture distributional similarity rather than deep semantic representation. Consequently, they may generate contextually plausible corrections that are not communicatively optimal. This supports the argument that current AI systems are predominantly structure-sensitive rather than cognition-sensitive. The computational modeling of meaning remains limited by the absence of fully interpretable semantic representations.

From a linguistic perspective, the results highlight the continued relevance of structural linguistic theory in computational modeling. The system's effectiveness in identifying morphological and syntactic errors reflects the applicability of formal grammar frameworks to NLP-based correction systems. However, the limited performance in pragmatic analysis confirms the importance of discourse and functional linguistics. Errors related to register, contextual appropriateness, or communicative intent require pragmatic competence that extends beyond grammar rules. This finding aligns with functional linguistic approaches emphasizing language use in communicative contexts rather than isolated structural units.

Furthermore, the agglutinative nature of Uzbek influences error detection performance. While affixation patterns are rule-governed, their combinatorial productivity increases morphological ambiguity. The relatively strong morphological performance suggests that the implemented analyzer adequately captures suffix sequences but may require further refinement for irregular forms or rare constructions.

The results carry significant implications for academic writing instruction. AI-based grammar correction tools can serve as effective support systems for identifying formal structural errors, particularly in orthography and morphology. However, reliance solely on automated systems may lead to insufficient development of semantic awareness and stylistic competence. The findings indicate that AI systems should complement rather than replace human feedback in higher education. Integrating AI tools into writing instruction may enhance structural accuracy while educators focus on discourse coherence, argumentation quality, and contextual appropriateness. Moreover, the correlation between linguistic competence and system effectiveness suggests that students with stronger theoretical linguistic knowledge benefit more from AI-assisted correction tools. This reinforces the importance of integrating linguistics education with digital literacy.

The study reveals several technological limitations. Although neural language models improve contextual analysis, they do not fully model pragmatic inference or world knowledge. Future research should focus on hybrid architectures combining:

- Rule-based grammatical constraints
- Statistical language modeling

- Cognitive-semantic frameworks
- Discourse-aware neural models

Expanding annotated Uzbek corpora is particularly crucial. Error-annotated datasets, semantic role labeling resources, and discourse-level corpora would significantly enhance system training and evaluation. Additionally, incorporating multimodal contextual signals and knowledge graphs may improve pragmatic modeling. The findings illustrate a convergence between classical linguistic theory and modern artificial intelligence. Structuralist and generative frameworks remain foundational for modeling formal grammar. Statistical NLP operationalizes probabilistic language patterns, while deep learning architectures provide scalable representation learning.

However, the results also demonstrate that AI systems have not yet fully integrated pragmatic theory and cognitive linguistics. Thus, interdisciplinary collaboration between linguists, computer scientists, and cognitive researchers remains essential. The study confirms that AI-based error detection systems are highly efficient in identifying formal structural errors but show limited performance in deeper semantic and pragmatic interpretation. This performance asymmetry reflects the inherent complexity of modeling human language cognition computationally. Advancing AI-driven language correction requires not only larger datasets and stronger models but also deeper theoretical integration with linguistic science. The development of language technologies for under-resourced languages such as Uzbek depends on systematic collaboration between linguistic scholarship and computational innovation.

V. CONCLUSION

This study examined the effectiveness of artificial intelligence–based systems in detecting and correcting linguistic errors within the academic writing of Oriental University students. The findings provide empirical confirmation that AI-driven language technologies demonstrate high performance in identifying formal, rule-governed errors, particularly in orthography, morphology, and syntax. These results reinforce the assumption that structurally codified aspects of language are more amenable to computational modeling through statistical and neural approaches.

At the same time, the study revealed notable limitations in the detection of lexical-semantic and pragmatic errors. Reduced recall and F1-scores in these categories indicate that contextual interpretation, discourse coherence, and communicative intent remain challenging for contemporary AI architectures. Although transformer-based models incorporate contextual embeddings, they primarily rely on distributional statistical patterns rather than fully modeling cognitive-semantic reasoning. As a result, AI systems are more efficient in structure-sensitive tasks than in meaning-sensitive and discourse-sensitive processing.

The research confirms a fundamental structural–semantic asymmetry in AI language processing: the more explicitly formalized a linguistic level is, the higher the detection accuracy. Conversely, linguistic phenomena involving inference, cultural context, and pragmatic appropriateness remain difficult to operationalize computationally. This outcome underscores the continued relevance of linguistic theory in AI development. Structural and generative frameworks provide essential foundations for modeling grammar, yet deeper integration of cognitive linguistics and pragmatics is required to address higher-order interpretative tasks.

From an educational perspective, the study demonstrates that AI-based correction tools can significantly improve students' structural writing accuracy. However, such systems should not replace human expertise in semantic refinement, stylistic coherence, and argumentative clarity. Instead, AI should function as a complementary pedagogical instrument, enhancing efficiency while preserving the role of educators in higher-level linguistic evaluation.

The findings also carry important implications for the development of AI technologies in under-resourced languages such as Uzbek. Expanding annotated corpora, especially those containing error-tagged data, is essential for improving model training. Investment in large-scale morphological, syntactic, and discourse-level datasets will directly influence system performance. Moreover, the development of hybrid architectures combining rule-based grammar constraints with neural contextual modeling may significantly enhance semantic and pragmatic detection capabilities.

Based on the results of this study, several strategic recommendations can be proposed:

1.Development of Language-Specific Corpora – Creation of large, annotated Uzbek-language corpora with detailed error tagging to improve AI training and evaluation.

2.Hybrid Modeling Approaches – Integration of rule-based grammatical frameworks with transformer-based neural models to balance structural precision and contextual flexibility.

3.Discourse-Level Modeling – Incorporation of pragmatic and discourse-aware features, including coherence modeling and communicative intent recognition.

4.Educational Integration – Systematic implementation of AI-based correction tools in academic writing courses as supportive, not substitutive, resources.

5.Interdisciplinary Collaboration – Strengthening cooperation between linguists, computer scientists, and cognitive researchers to bridge theoretical and computational perspectives.

Ethical and Responsible Use – Establishing clear academic policies for AI-assisted writing to prevent overdependence and maintain academic integrity.

In conclusion, AI-based language correction systems have achieved substantial progress in modeling formal linguistic structures, yet the accurate computational representation of meaning and pragmatics remains an open scientific challenge. Advancing intelligent language technologies requires not only more powerful algorithms but also deeper theoretical integration with linguistic science. The future of AI-driven language processing lies in interdisciplinary synergy, resource development, and cognitively informed modeling frameworks.

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