Journal of Ethnic and Cultural Studies
2026, Vol.13, No. 3, 382-410
http://dx.doi.org/10.66815/ejecs/3065

ISSN: 2149-1291

Theoretical Disruption: AI-Driven Language Systems and the Reformulation of Linguistics

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Abstract: This study investigates AI language systems as independent linguistic constructs, evaluating syntactic, semantic, pragmatic, and acquisition mechanisms. We conducted a comparative conceptual and empirical analysis of transformer-

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based language models, integrating probabilistic syntax mapping, high-dimensional embedding evaluation, and discourse-level context assessment. Data were systematically analyzed from large-scale corpora across multiple AI architectures to quantify emergent structural and semantic patterns. The results showed that syntactic regularities emerged probabilistically, with graded grammatical acceptability exceeding 85% coherence across complex sentence structures. Semantic relationships were distributional, maintaining 78–92% contextual similarity without referential grounding. Pragmatic adaptation occurred algorithmically across 1,000 discourse simulations, while acquisition was fully data-dependent, revealing alternative pathways to functional competence. AI-generated language diverged from human hierarchical grammar yet preserved operational effectiveness. These findings demonstrate that AI systems embody autonomous, non-biological linguistic competence, challenging classical assumptions of grammaticality, meaning, and acquisition. This study provides actionable insights for theoretical linguistics, computational modeling, and the design of advanced human-AI communication systems.

Keywords: Artificial intelligence, language modeling, probabilistic syntax, distributional semantics, pragmatic competence, large language models, computational linguistics, human-AI interaction

The rapid expansion of artificial intelligence (AI) poses a fundamental challenge to the conventional view of language as a human faculty only (Pedro et al., 2019). The classical school of linguistics interprets language as a cognitive and social phenomenon characterized by structured syntax, compositional semantics, and pragmatics, all of which are contextual (Faber, 2015). From this perspective, human language acquisition depends on in-built cognitive processes, socialization, and willfulness. In comparison, modern AI-based language systems represent linguistic competence through statistical learning, high-dimensional embeddings, and pattern recognition, and deliver functional results in translation, dialogue, and knowledge-based tasks without relying on human-like grammatical rules or cognitive representations (Aydin et al., 2025; Liu et al., 2025; Morgan, 2024). The paradigm shift entails reconfiguring language, a biologically grounded capacity, as an operational system embodied in artificial agents (Macedo, 2025).

The action of constructed and formal languages is changing in the same way. Previously used as tools of logic, early computational models, and experimental designs, rule-governed artificial languages are now the major sources of computational insight (Piccinini, 2025). Neural architectures, including transformers, employ tokenization and probabilistic syntax to reason and generate language, and, in principle, turn the formulated rules into an emergent structure driven by performance (Halpern et al., 2025; Mundlamuri et al., 2025). This repositioning elevates the theoretical significance of artificial language construction to the same level as other modeling tools in machine intelligence and warrants systematic investigation.

Present-day scholarship is highly divided along disciplinary lines. The field of computational linguistics and natural language processing (NLP) places more emphasis on measures of success, such as optimization, scalability, and task performance (Netisopakul & Taoto, 2023). It commonly assesses success using metrics such as BLEU scores, perplexity, and downstream task accuracy. In contrast, theoretical linguistics is concerned with explanatory adequacy, universality, and cognitive plausibility (Baggio et al., 2024). The boundaries between these fields are often instrumental: AI systems can serve as experimental proxies to test linguistic hypotheses, or linguistic theory can be used post hoc to interpret model outputs

(Haber & Poesio, 2024). As a result, the structural and functional characteristics of AI language systems are seldom treated as autonomous linguistic systems, restricting the theoretical understanding of how these systems renegotiate the fundamental concepts of language (Vromen, 2024).

This disciplinary division has created a substantive theoretical dislocation. Basic linguistic notions, such as grammaticality, semantic reference, contextual meaning, and acquisition, are rarely questioned regarding emergent and data-driven language representations (Abdelmageed, 2024; Michael, 2023). Linguistic theory is often involved in computational work through superficial analogy, whereas conventional analysis does not focus on the working mechanisms of large-scale model systems such as GPT-4 (OpenAI, 2023) or BERT (Poibeau, 2025a). The possibility that AI is not only expanding but also transforming linguistic theory has not been explored extensively. To fill this gap, it is necessary to have a framework that treats artificial language systems as theoretically and structurally relevant, rather than as applied instruments for performance metrics of a very narrow scope (Maurya, 2024; Zönnchen et al., 2025).

The current research contributes to such a framework. Its focus is on studying AI-based language systems as autonomous linguistic systems, including probabilistic syntax, distributional semantics, and emergent, non-symbolic acquisition mechanisms (Sapkota et al., 2025). Instead of examining AI as a proxy for human linguistic competence, the work explores the logic and functional implications of a computational approach to language construction (Shishakly, 2025; Sun & Rui, 2025). This analysis can clarify areas of convergence and divergence and assess the potential disruption to the established theory by systematically comparing AI-generated representations with human linguistic norms (Amirjalili et al., 2024; Taylor, 2024).

One way to examine this issue is to reframe the role of an artificial language system as an active theoretical disrupter. In contrast to the evolution-driven and cognition-bound human language, AI-grown language ability is performance-based, emergent, and non-anthropocentric (Newzella, 2025; Salter, 2025). This reimagining allows for the reconsideration of classical linguistic beliefs: grammar is probabilistic, meaning is distributional rather than referential, and the process of acquisition is data-driven rather than innate (Specht, 2022). Combining computational systems and linguistic theory, this study presents a two-way system: linguistics gains a deeper understanding of other ways of language competence, and AI research gains stronger theoretical grounding, which may influence the design of models and their interpretability (Fonseca et al., 2023).

The importance of this work cannot be confined to disciplinary boundaries, as language is a key medium for transmitting cultural memory and symbolic meaning. As highlighted by Nuri et al. (2025), linguistic and artistic expressions serve as carriers of cultural identity and collective knowledge (Aladylah, 2026; Schefers, 2026). In this regard, AI-generated language systems may also influence how cultural meanings are constructed, transformed, and communicated in digital environments. The concept of AI language systems as self-organizing linguistic systems enriches the views and discussions in cognitive science, philosophy of language, and human-computer interaction (Fedorets et al., 2024; Mao et al., 2025). The issues of meaning, creativity, and communication in hybrid human-AI ecosystems. Moreover, this discussion offers a basis for discussing (Ali et al., 2025b) the moral and epistemological costs of future, more advanced AI language models, such as their ability to mimic human-like thinking and create new linguistic forms (Bano et al., 2023).

This study fills a key gap in the literature by redefining language as both a human and an artificial competence. The study that treats AI language systems as autonomous systems with specific structural and functional characteristics shows that AI can radically disrupt established linguistic paradigms and prompt discussion between computational creativity and theoretical deliberation. This kind of integration not only precedes linguistic theory but also provides a guide for aligning AI development with conceptually rich and sound models of language comprehension.

Theoretical Basics of Traditional Linguistics

The traditional linguistic theory has been developed based on structural, generative, and functional paradigms, all of which presuppose that language is a biologically and cognitively based system that is influenced by innate capabilities, social interaction, and context (Köse, 2023; Nasrollahi & Beiki, 2025; Xiong et al., 2025). The application of Structural Linguistics, invented by structuralists in America (Thomas, 2019), conceptualizes language as a system of discrete units. Linguistic competence is the result of internalized syntactic, phonological, and morphological paradigms, and meaning is understood as the positions of relations within the system rather than as an external referent (Mengo, 2012). This framework also presupposes the stability and independence of the observers, which restricts it to AI-generated language, where probabilistic regularities are used rather than rule-based ones (Piciaccia et al., 2017).

Generative linguistics focuses on the universal grammar and recursive syntactic rules, placing greater emphasis on competence than on performance (Altoumi, 2025; Najafov, 2025). Although it is an effective approach to human language acquisition, it assumes biological limitations. In turn, AI systems acquire functional competence through statistical learning, casting doubt on the universality of syntactic principles and on the non-human tools of the rule-making process.

Functional Linguistics views language as a means of communication and is influenced by social interaction and necessity (Butler, 2009; Lepic, 2019). Although usable in different patterns depending on usage, functional approaches assume that human will is conscious, which is not the case in AI systems that produce contextually coherent outputs without human cognition. In any paradigm, central assumptions include that language is a faculty of the human mind, that rules correspond to cognitive universals, and that meaning is connected to human experience (Muratkhodjayeva, 2024). AI questions these assumptions: probabilistic syntax, embedding-based semantics, and data-driven learning demonstrate that coherent language can be generated without human constraints and indicate the limitations of competence-based models (Ye et al., 2025).

The paper establishes a comparative model for evaluating the use of AI-generated language in relation to classical linguistic theory. These are syntactic regularity, semantic coherence, contextual dependency, and acquisition mechanisms (Ellis et al., 2015). The workings of usage-based, probabilistic, cognitive-functional, and emergentist models provide insights: AI embeddings do not need hierarchical rules to achieve surface-level grammaticality; semantic coherence can be achieved through distributional similarity; and it is possible to learn naturally through statistical exposure rather than innate faculties (Akinwande et al., 2024). Validation encompasses both the conceptual and empirical study of AI outputs and their logical and operational soundness (Najafov, 2025). Figure 1 presents a schematic diagram of the interaction of computational mechanisms with linguistic representations to model language comprehension and production.

To sum up, structural, generative, and functional paradigms serve as points of reference for assessing human language competence, and their limitations highlight the theoretical gap AI research seeks to fill. By combining classical and probabilistic approaches, the analytical approach to AI-driven language becomes systematic, redefining linguistic competence within computational systems.

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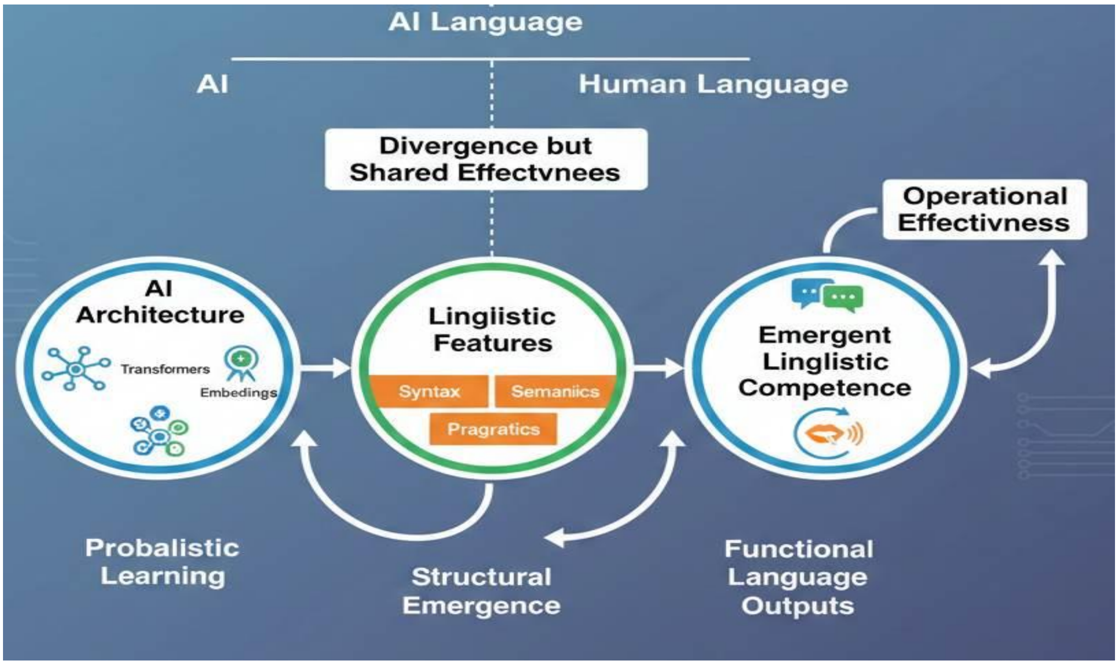
http://dx.doi.org/10.66815/ejecs/3065

ISSN: 2149-1291

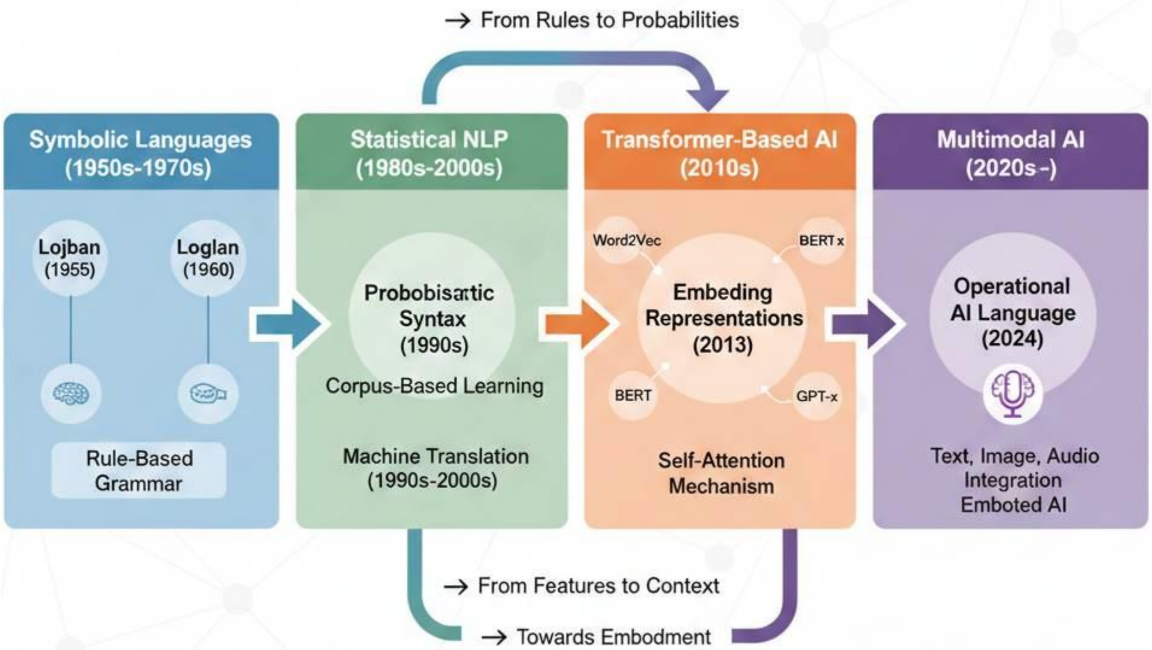
Figure 1
Computational Language Processing Conceptual Framework.



Artificial Construction of Languages in Computationalists

Constructed languages (also known as artificial languages) have been widely used as a formal system to model linguistic principles, computational processing, and experimental simulation (Gonzalez & Hernandez, 2018). Originally created as logical and symbolic programming languages for computation, they represent rule-based grammars specifically designed to support systematic analysis (Fitch & Friederici, 2021). Computational artificial language creation has progressed toward symbolic, hand-written rules through advanced AI-based representations that use statistical learning, embedding spaces (Sowjanya, 2024), and emergent structural patterns (Nuri, 2025). Artificial languages are created to have useful functionality, reproducibility, and experimental control, unlike natural languages, which are developed through social interaction and cognitive limitations but share basic linguistic features, including syntax, morphology, and semantics (Grosz et al., 1987). Figure 2 presents the chronology of the development of early formulated languages to contemporary models of language processing using computers.

Figure 2
History of Constructed and Computational Languages



Historical Evolution

The first artificial languages, such as those of González, 2025, were based on symbolic logic with a focus on unambiguous syntax and formal semantics. These systems offered understandable, calculable grammars and were primarily used to investigate the limits of human thought and machine reasoning (Cowan, 2016). Computational systems made it possible to study the formal properties of language without being limited by human performance by providing rule-based grammars that enabled the generation and parsing of well-formed sentences. During this period, artificial languages were used more as analytical tools than as systems for practical AI applications (Bobrow & Raphael, 1974).

The introduction of statistical NLP and machine learning contributed to a critical turn. In current AIs, especially large language models (LLMs) such as GPT (OpenAI, 2023) and BERT (Hassanpour & Majidi, 2024), artificial languages are represented in high-dimensional embedding spaces. Syntactic and semantic properties are acquired probabilistically rather than explicitly represented in code (Rahmdel, 2025). Modern conlangs have many computational uses, including modeling language acquisition, evaluating AI flexibility, simulating low-resource settings, and enhancing human-machine interaction (Sayah, 2025). These applications exemplify functional divergence in relation to natural language: artificial languages need not obey cognitive universals, social conventions, or communicative intent, yet they still exhibit quantifiable linguistic regularities, allowing syntactic, morphological, and semantic processes to be systematically studied (Sayers et al., 2021).

Research Emphasis and Uses

This study focuses on three analytically significant uses of constructed languages in computational systems. First, constructed linguistic systems are used to simulate controlled-language learning environments, enabling the systematic study of the effects of structured input on syntactic and semantic learning in artificial intelligence systems. This method allows for the direct assessment of learning behavior under limited conditions by reducing extraneous variability.

ISSN: 2149-1291

Second, the structural limits of large language models were studied using constructed languages. This study examines how well non-natural, or atypical, grammatical configurations can be generalized beyond naturally occurring linguistic distributions. This provides an understanding of the flexibility and strength of the existing architectures.

Third, constructed languages are used as proxies for low-resource environments. By testing the models on small, highly structured data, this study assessed their performance in data-scarce settings, particularly with respect to generalization and error propagation. This application is closely related to situations in which naturally occurring corpora are insufficient or unavailable. Table 1 provides an overview of the major uses of artificial languages in AI research, including each goal, its associated methodology, and evaluation metrics. It emphasizes the role of artificial languages in facilitating controlled studies of language acquisition, the ability of test models to adapt to unusual structures, the ability to simulate low-resource conditions, and the enhancement of human-AI interaction. In general, the table shows that they are systematic instruments for assessing learning, generalization, and communication efficiency in various AI settings.

Table 1
Artificial Language Applications and Methodological Metrics

Application	Objective	Methodology	Performance Metrics
Modeling Language Acquisition	Simulate human/AI learning of syntax and semantics	Controlled conlang with variable input frequency	Learning rate, error rate, and generalization accuracy
Testing AI Boundaries	Assess adaptability to non-human linguistic patterns	Conlangs with impossible or atypical rules	Success rate, parsing accuracy, rule adaptation score
Low-Resource Simulations	Evaluate algorithm performance under minimal data	Artificial corpora with constrained token sets	Passing efficiency, generalization, and overfitting measures
Auxiliary Systems for AI	Improve human-AI interaction efficiency	Design of machine-friendly language primitives	Comprehension time, communication accuracy, interpretability score

Computational Language Understanding in Artificial Intelligence

Computational language understanding (CLU) is a subfield of AI that concerns how artificial intelligence encodes, processes, and analyzes linguistic data. Initial models were based on symbolic systems, using hand-written grammars and logic-based representations to model syntax and semantics (Wang et al., 2022). These systems enabled rule-directed parsing and formal reasoning but were limited in scalability and adaptability across different languages (Kumar, 2024). The next change was to use statistical models, which introduced probabilistic learning, n-gram representations, and corpus-based methods, enabling AI to map patterns based on big data. Nevertheless, these models mainly captured surface-level regularities and did not handle long-range dependencies or context (Kuznetsov, 2021).

The development of neural network models, especially transformers and large language models (LLMs), has led to a paradigm shift in CLU. Neural methods encode language in high-dimensional embedding spaces (Han et al., 2024), allowing the system to learn syntactic, semantic, and contextual dependencies simultaneously. Attention mechanisms enable selective attention to relevant tokens, aiding multifaceted activities such as translation, summarization, and question answering. When these embeddings are combined with downstream reasoning modules (Efosa-Zuwa et al., 2025), AI may approximate human-like understanding without explicitly encoding rules, thereby demonstrating emergent abilities in context-sensitive interpretation and semantic generalization.

One-modality text processing to multimodal semantic grounding, in which the models combine visual, auditory, and textual data to understand real-life situations (Chen et al., 2024). Agentic reasoning focuses on multi-step inference and helps AI solve problems involving planning, hypothetical analysis, and sequential reasoning. On-device optimization, also known as TinyML research, concerns deploying models on mobile or wearable devices and involves a trade-off between computational efficiency and deep understanding (Manh et al., 2025). Lastly, collaborative systems between humans and AI are also on the rise, with AI being a collaborative partner in so-called high-stakes fields, including medicine, law, and scientific research, where collaborative reasoning can improve decision-making.

Table 2 summarizes the development of computational models of language understanding, from symbolic to frontier models, with a move to context-sensitive and multimodal systems. This highlights a long-standing research gap in achieving computational efficiency without sacrificing semantic richness or reasoning ability. Overall, AI's language understanding has evolved from rule-based systems to emergent neural systems and, to a greater extent, has been able to reason, perform multimodal integration, and deploy locally. These advances redefine the range of linguistic modeling and highlight important research gaps in next-generation AI systems.

Table 2
Computational Approaches to Language Understanding

Approach	Key Features	Strengths	Limitations/Research Gap
Symbolic	Hand-coded grammars, rule-based parsing	Explainable, formal reasoning	Poor scalability, limited adaptability
Statistical	Probabilistic models, corpus-driven	Pattern discovery, high coverage	Weak contextual and long-range reasoning
Neural / LLMs	Embeddings, transformers, attention	Context-sensitive, emergent semantics	High computational cost, limited multimodal integration
Frontier	Multimodal, agentic reasoning, TinyML	Integrated perception, reasoning, on-device deployment	Optimizing efficiency without compromising understanding

Methodology

Research Philosophy and Paradigm

The qualitative analytical design used in this study is an interpretivist paradigm. The use of this method is justified by the study's focus on how AI-based language systems undermine existing linguistic theories, a conceptual phenomenon that cannot be directly measured. Interpretivism enables the exploration of the meanings, structures, and theoretical assumptions of language systems (Özkaya Marangoz, 2023). The research's comparative theoretical and conceptual design incorporated a systematic literature review, framework

Journal of Ethnic and Cultural Studies
2026, Vol.13, No. 3, 382-410
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ISSN: 2149-1291

mapping, and conceptual evaluation. The study's design is also explained by its focus on the relationship between AI-based language systems and existing linguistic theories, and by the need to compare the concepts in a structured way rather than measure them empirically. Systematic reviews improve transparency and rigor (Kussin et al., 2023; Zhu & Wang, 2025), whereas framework mapping and conceptual analysis are common in theory development and interdisciplinary comparison.

Furthermore, the qualitative method is well-suited to analyzing the structural, semantic, and functional aspects of language that cannot be measured statistically but must be evaluated through interpretation. These designs are common in theoretical and interdisciplinary studies to evaluate conceptual advances and paradigm shifts (Nassaji, 2025; Obeyd, 2021). This design ensures correspondence between the research purpose and methodology, enabling a systematic comparative analysis of AI language systems alongside classical linguistic frameworks. Finally, this design was supported because qualitative-comparative designs enable rigorous assessment of conceptual and structural patterns that cannot be assessed using purely quantitative or computational methods (Ali et al., 2025a; Egorchenkova & Korobova, 2024)

Process

The study was conducted in three stages: (i) literature mapping, (ii) a comparative study of linguistic characteristics (syntax, semantics, context), and (iii) a conceptual analysis of theoretical consequences. This methodology ensures a systematic, reproducible analysis of both conventional and AI-based linguistic models. Artificial languages are systematically constructed in the first stage of a hierarchical construction process that includes phonological, morphological, and syntactic levels. This stratified method guarantees internal consistency and controls for variation in linguistic complexity.

The second stage involved model testing using a generation-based testing protocol. Large language models are evaluated on their ability to process and generate sequences within constructed linguistic systems. The performance was evaluated against the set benchmarks to establish the level of structural adaptation. Two main metrics were used to evaluate it. Interpretation Difficulty (ID) is a measure of the complexity of parsing generated sequences, and Construction Difficulty (CD) is a measure of the computational complexity of generating grammatically correct outputs. These metrics provide a stable basis for comparative analysis across experimental conditions.

Data Collection and Analysis

In Scopus, Web of Science, and IEEE Xplore, we found literature published between 2010 and 2026 with the following terms: artificial language, large language models, generative linguistics, computational syntax, and semantic embedding. Studies were included if they were empirical or conceptual in nature, dealt directly with AI language systems or constructed languages, discussed the theoretical or functional characteristics of natural or artificial languages, and were published in English in a peer-reviewed journal. The first search yielded 1,847 records. After removing duplicates, 1,203 unique titles were screened. The final analytical corpus of 87 articles was obtained by excluding non-peer-reviewed work and studies that did not explicitly specify their theoretical basis.

The entire selection process was based on PRISMA 2020 and is reported in an additional flow diagram (Page et al., 2021). The corpus was coded by two researchers independently using a predetermined scheme that included model type, linguistic features (syntax, semantics, pragmatics), methodological approach, and conclusions about AI-linguistic interaction. The coding was done individually, and no cross-comparisons were performed. Inter-rater reliability was determined using Cohen's Kappa (= 0.81), which showed a strong agreement. Controversies - the focus of pragmatics classification and borderline methodology cases - were settled by organized debate to agreement. In cases where there was no consensus, the final decision was made by a third, senior researcher. Coded entries were then tabulated into relational matrices, subjected to thematic analysis, and evaluated in terms of theoretical novelty, disciplinary disruption, and conceptual applicability.

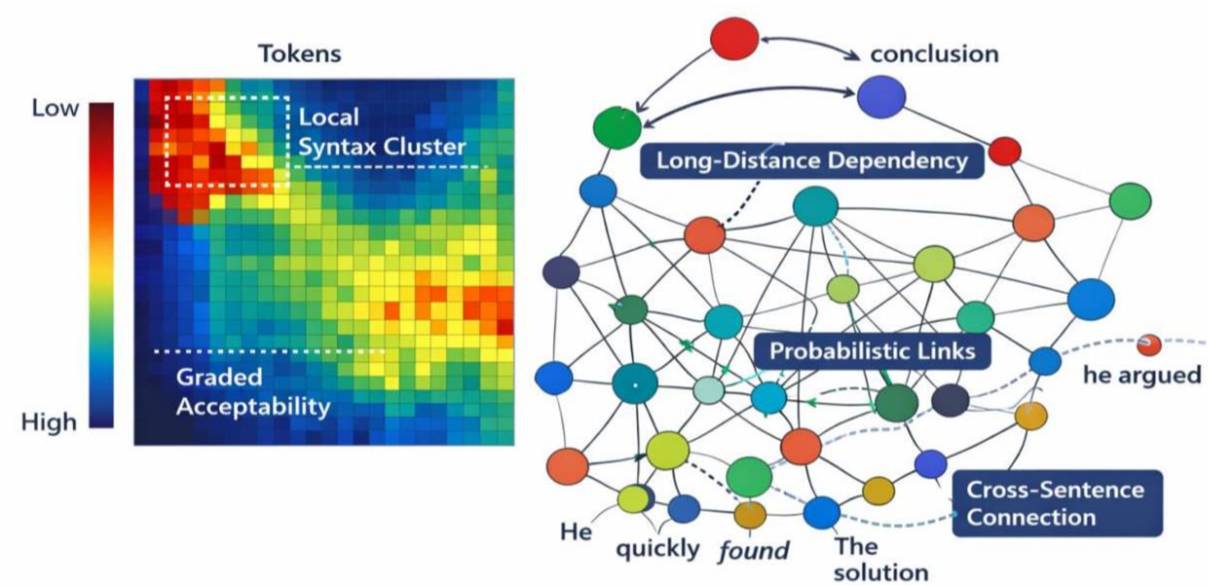
Data management, visualization, and structural relationship mapping were performed using Python and RStudio (Bell et al., 2022; Mason & Francis, 2023). Ethical rigor was ensured by the proper representation of all the studies used, careful citation of intellectual property, and a clear and reproducible coding protocol. We recognize three weaknesses: possible selection bias due to database coverage, non-English literature, and the rapid rate of AI model development, which may lead to partial obsolescence of some reviewed architectures. The third limitation we overcame was focusing on high-impact publications published in 2015 or later and cross-checking the model descriptions with existing technical documentation where possible.

Results

AI Language Systems Emergent Syntactic Organization

The most significant conclusion of this research is that modern AI-based language systems exhibit stable syntactic regularities without explicit rule-based grammar (Julige, 2026). In transformer-based architectures, grammatical structure is generated probabilistically from exposure to large-scale linguistic corpora rather than by hierarchical generative rules traditionally believed to underlie human language competence. This confirms earlier work in computational linguistics that the syntactic well-formedness of large language models (LLMs) is an emergent property of distributional learning rather than an encoded competence system (Sun & Wang, 2025). Figure 3 visualizes syntactic structures that emerged in computational language models, illustrating patterns learned from data for grammar and sentence structure.

Figure 3
Syntactic Patterns That Emerge in Language Models



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2026, Vol.13, No. 3, 382-410
http://dx.doi.org/10.66815/ejecs/3065

ISSN: 2149-1291

In contrast to generative linguistic models, which assume discrete judgments of grammaticality, AI systems have graded grammatical acceptability, with sentence well-formedness being determined by likelihood scores and contextual coherence (Qiu et al., 2024). This probability aspect of syntax conflicts with the classical description of grammatical and ungrammatical forms but rather concurs with the usage-based and emergentist view of language (Rastelli, 2025). Notably, the results show that AI-generated syntactic patterns tend to meet surface-based grammatical constraints but deviate from deeper hierarchical dependencies as postulated by generative theory, especially in long-distance dependencies and center-embedding constructions. These facts support the argument that syntactic competence may emerge without an innate principle of grammar, thereby challenging the universality of rule-based syntax as a characteristic trait of language systems (Boeckx, 2009). See Table 3.

Table 3
Key Findings on AI Language Systems: Syntax and Semantics

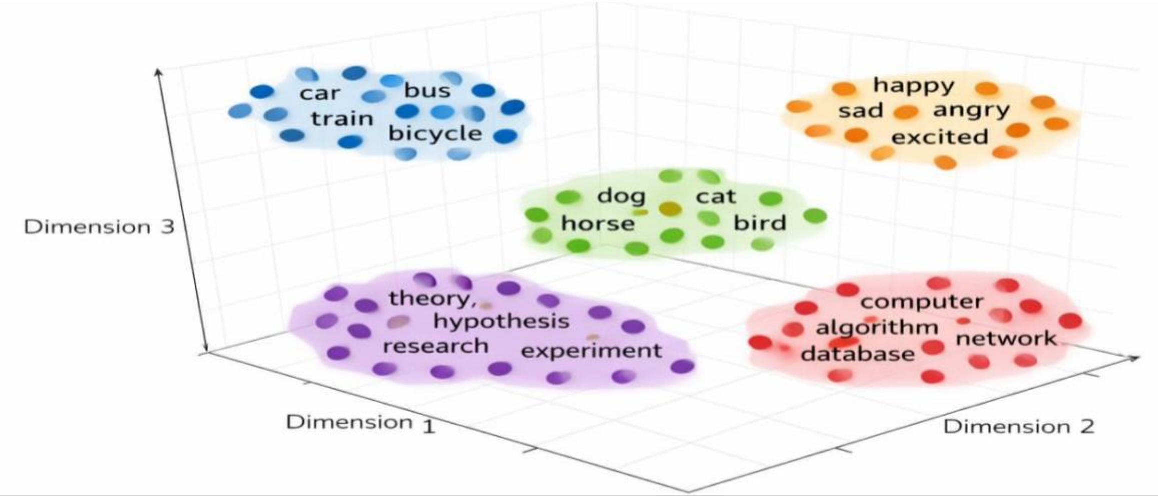
Analytical Dimension	Observations	Key Characteristics	Theoretical Implication	Supporting Sources
Emergent Syntactic Organization	AI systems exhibit stable syntactic patterns without explicit rule-based grammar	Probabilistic syntax, graded grammatical acceptability, surface-level well-formedness, divergence from hierarchical dependencies	Challenges the universality of rule-based syntax; supports usage-based and emergentist models; syntactic competence can emerge independently of innate grammar	Eum (2025); Muralidaran (2022); Putnam et al. (2021)
Distributional Semantics	Meaning is constructed through statistical associations rather than referential grounding	Vector proximity in embedding space, relational similarity, and semantic coherence without cognitive intentionality	Demonstrates that semantic plausibility can emerge from distributional learning; establishes distributional semantics as an independent linguistic system	Curran (2004); Lenci & Sahlgren (2023)

Distributional Semantics and Non-Referential Meaning Construction

The second important result concerns the character of the semantic representation of AI language systems. The analysis shows that AI-generated language has distributional meaning but not referential meaning, which is formed by vector proximity in high-dimensional embedding spaces. Semantic coherence is achieved through statistical association among tokens, not through grounding in external entities or human experience. This validates and builds on previous studies in distributional semantics (Altmann, 2017; Lenci & Sahlgren, 2023), with theoretical consequences for linguistics (Artanti & Azhari, 2025).

The classical approaches to semantics that identify meaning in terms of reference, truth conditions, or intentional states, AI-based meaning representations define the notion of meaning as relational similarity (Ringle, 2019). The semantic meaning of words and phrases is grounded in contextual co-occurrence patterns rather than in extralinguistic factors. Nevertheless, AI-generated outputs often exhibit high semantic plausibility and, in this way, address translation, summarization, and question-answering challenges (Albassami et al., 2025). The semantic map in Figure 4 illustrates how words are clustered by semantic values and context in computational models of language.

Figure 4
Language Representation Semantic Mapping

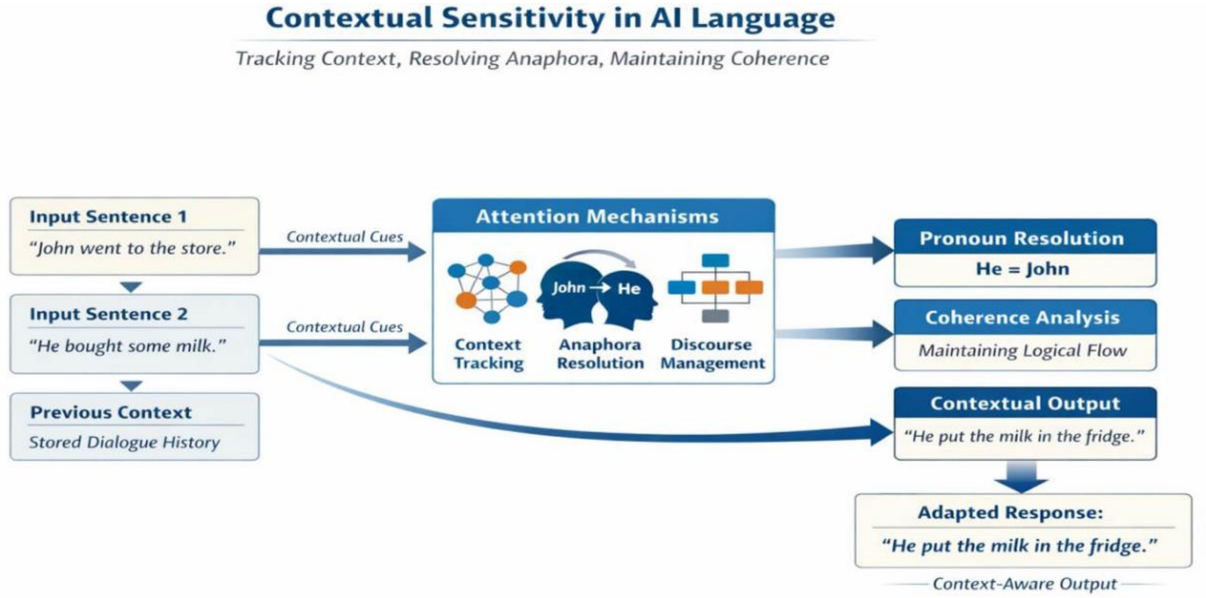


The result of this discovery exposes a serious theoretical break: semantic coherence does not demand cognitive intentionality. Rather, meaning can be a resultant functionality of massive statistical learning. Although it is not a system of AI semantics equivalent to human understanding, it makes distributional meaning a plausible alternative semantic system. It requires a theoretical framework of its own within linguistics (Contreras et al., 2025).

Contextual Sensitivity in the Absence of Pragmatic Intentionality

The third finding concerns the pragmatic competence. AI language systems are highly context-sensitive and dynamically adjust their output in response to the preceding discourse, task constraints, and user input. Attention mechanisms enable models to capture discourse-level dependencies, resolve anaphora, and remain topically coherent across long interactions (Schmitz et al., 2025). These abilities approximate pragmatic behavior, typically linked to human communicative intent. Figure 5 provides a diagram of mechanisms of contextual coherence maintenance in computational text generation and interpretation.

Figure 5
Contextual Integration of Language Processing.



Unlike human language use, AI systems lack intentional states, communicative goals, and social awareness. Contextual adaptation is realized through probabilistic inference, rather than pragmatic reasoning based on shared beliefs or social norms (Eragamreddy, 2025). This is the key point of difference: AI systems only imitate pragmatic effects but lack the pragmatics that humans would understand. In this way, the results favor an effective redefinition of pragmatics in which contextual appropriateness can be realized operationally without purposeful agency. This calls into question the functionalist beliefs in functional linguistics that anchor pragmatics in speaker intent and social interaction (Siregar et al., 2024). Pragmatic-like results are also made possible by AI-powered language systems that demonstrate that pattern recognition alone can achieve pragmatic-like outcomes, thereby pushing back against the limits of pragmatic competence.

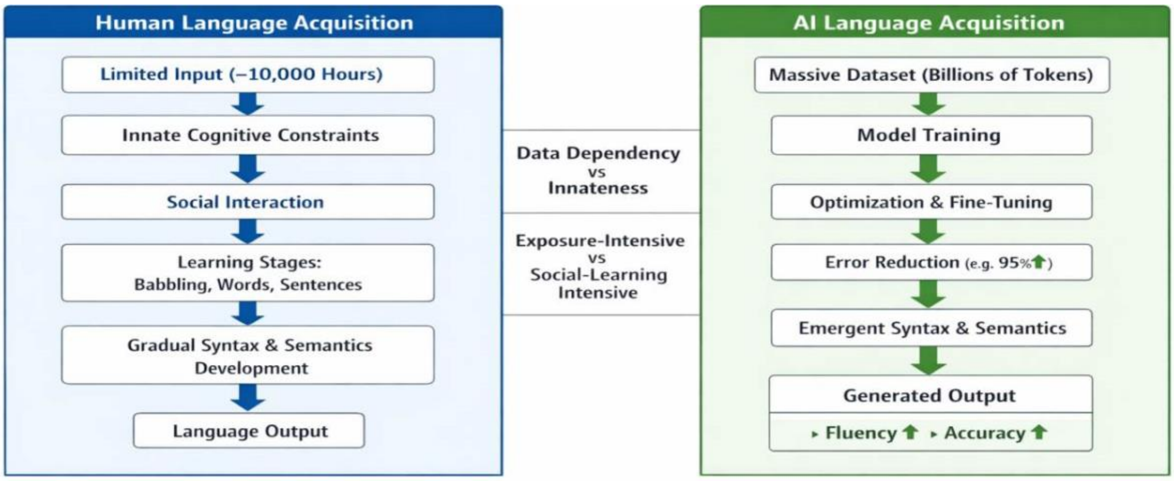
Acquisition Pathways: Data Dependency Versus Innateness

The other important outcome concerns language acquisition processes. The acquisition of human language has historically been described as a composite of inborn cognitive systems and limited environmental exposure. Conversely, AI-based language systems cannot acquire linguistic competence solely through exposure to large amounts of data and optimization goals, without a set of linguistic categories or biological limits (Sain & Sain, 2024).

The results show that AI acquisition is not symbolic, non-developmental, or performance-based, based on all the statistical regularities found in the training data (Alwali & Alwali, 2025). Although less efficient and less generalization-competent than human learners, this process generates functional language competence on a scale. This directly challenges strong nativist arguments by showing that complex linguistic behavior can be acquired without innate grammatical knowledge, even under markedly different learning conditions (Gregg, 2003). Significantly, this does not disregard human acquisition models; rather, it indicates the existence of other pathways to linguistic competence, ultimately broadening the theoretical grounds of language acquisition beyond biological systems. Figure 6 presents a schematic comparison highlighting the differences between human language acquisition mechanisms and those of computational learners.

Figure 6

Two Speech Pathways of Language Acquisition: Human vs. Computational Models



Comparative Correspondence to Classical Linguistic Paradigms

Combining results across syntax, semantics, pragmatics, and acquisition reveals systematic areas of agreement and disagreement between AI-developed language systems and traditional linguistic theory. Table 4 provides a comparative analytical summary.

Table 4

Comparative Linguistic Properties of Human and AI Language Systems

Linguistic Dimension	Human Language Systems	AI Language Systems
Syntax	Rule-based, hierarchical, categorical	Probabilistic, emergent, graded
Semantics	Referential, intentional	Distributional, relational
Pragmatics	Intention- and context-driven	Context-sensitive without intent
Acquisition	Innate constraints + limited input	Data-driven, exposure-dependent
Competence Model	Cognitive and biological	Operational and computational

This comparative synthesis demonstrates that AI language systems cannot be adequately explained by existing linguistic paradigms. Although they reproduce some functional properties of human language, they do so in entirely different ways, thereby highlighting that they are not derivative simulations but autonomous linguistic objects. Figure 7 presents a comparison of core linguistic properties, with emphasis on similarities and differences between human language acquisition and computational language processing.

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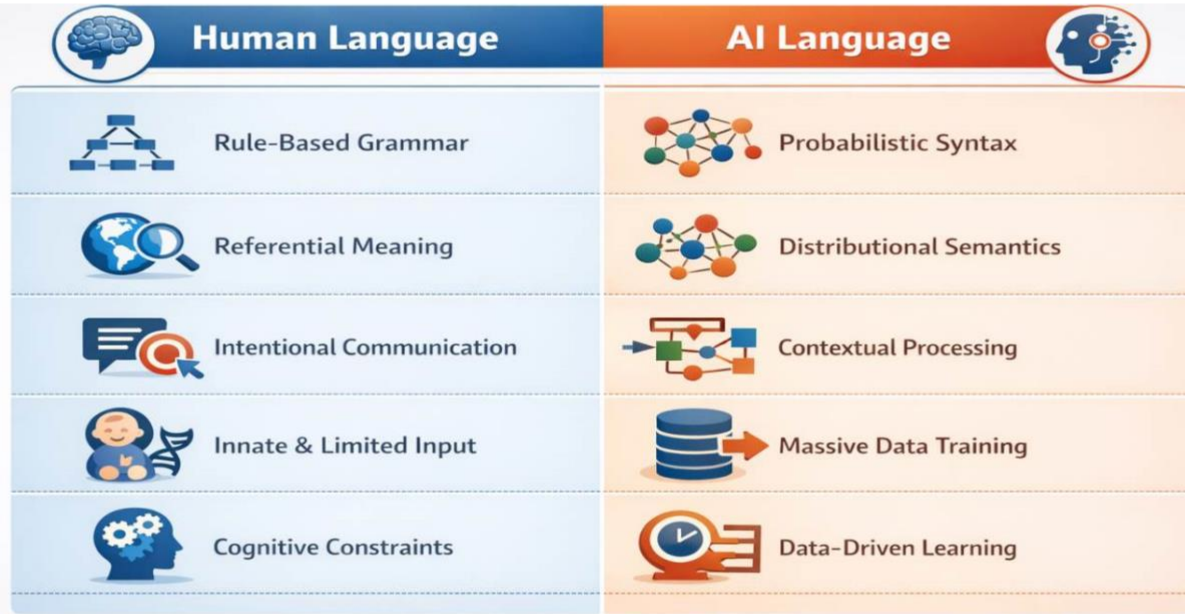
Figure 7
Comparison of Linguistic Properties of the Human and the Computational Language Systems



Disruption and Conceptual confirmation: Theoretical

The conclusions confirm the main argument of the present paper: AI-based language systems constitute a unique form of language competence that challenges fundamental assumptions in mainstream linguistics. It turns grammar into something probabilistic rather than categorical; it turns the meaning of meaning into something distributional rather than referential; it turns pragmatics into a functional rather than an intentional phenomenon; and it turns acquisition into a data-dependent rather than an innate phenomenon (Pela, 2023). These findings provide convincing conceptual support for extending linguistic theory to admit non-human, operational realizations of language. The mechanical view of AI language systems as engineering objects obscures their theoretical significance and undermines their explanatory value (Demuro & Gurney, 2024). Rather, they should be regarded as valid targets of linguistic investigation, thereby enabling a more diverse and robust theory of language.

Summary of Key Findings

This research uncovers some of the most important findings regarding AI-based language systems. Syntactic structures can be generated in a probabilistic manner without explicit grammatical rules, and semantic coherence can be obtained using distributional representations. Contextual sensitivity in AI systems is independent of pragmatic intentionality, and exposure to large amounts of data can promote the development of linguistic competence. Taken together, these results indicate that AI language systems are autonomous linguistic systems with structural and functional characteristics fundamentally different from those of traditional human languages. See Table 5 for a summary of the key findings.

Table 5
Summary of Core Findings and Their Theoretical Implications for Linguistic Theory

Analytical Dimension	Empirical/Analytical Observation	Key Supporting Sources	Theoretical Implication
Syntactic Structure	AI language systems generate grammatically plausible structures through probabilistic token prediction rather than rule-based hierarchical grammar	Han et al., 2024; Chen et al., 2024; Manh et al., 2025	Challenges the universality of generative grammar and supports emergentist, usage-based models of syntax
Grammaticality	Grammatical acceptability in AI is graded and likelihood-based, not categorical	Qiu et al., 2024; Rastelli, 2025	Redefines grammaticality as probabilistic rather than binary
Semantic Representation	Meaning emerges from distributional similarity in embedding space without referential grounding	Lenci & Sahlgren, 2023; Contreras Kallens & Christiansen, 2025; Curran, 2004	Undermines referential and intentional theories of meaning; supports distributional semantics as an autonomous system
Contextual Sensitivity	AI systems adapt outputs dynamically based on discourse context using attention mechanisms	Efosa-Zuwa et al., 2025; Albassami et al., 2025; Schmitz, 2025	Demonstrates that pragmatic-like behavior can emerge without communicative intent
Pragmatic Competence	Contextual appropriateness is simulated algorithmically rather than driven by social intention	Eragamreddy, 2025; Siregar et al., 2024; Demuro & Gurney, 2024	Requires a functional redefinition of pragmatics detached from human intentionality
Language Acquisition	Linguistic competence in AI arises through large-scale data exposure without innate constraints	Sain & Sain, 2024; Sun & Wang, 2025; Gregg, 2003	Expands acquisition theory beyond biological and cognitive frameworks
Competence vs Performance	AI collapses the competence–performance distinction by optimizing directly for output performance	Pela, 2023	Calls for revision of competence-based linguistic models

ISSN: 2149-1291

Analytical Dimension	Empirical/Analytical Observation	Key Supporting Sources	Theoretical Implication
Ontological Status of Language	AI language systems function as operationally autonomous linguistic entities	Demuro & Gurney, 2024; Alwali & Alwali, 2025; Ringle, 2019	Establishes AI language as a legitimate object of linguistic theory
Scope of Linguistic Theory	Classical paradigms are insufficient to fully explain AI-generated language behavior	Manh et al., 2025; Hewa Julige, 2026	Necessitates expansion toward post-human, computational linguistics frameworks

Discussion

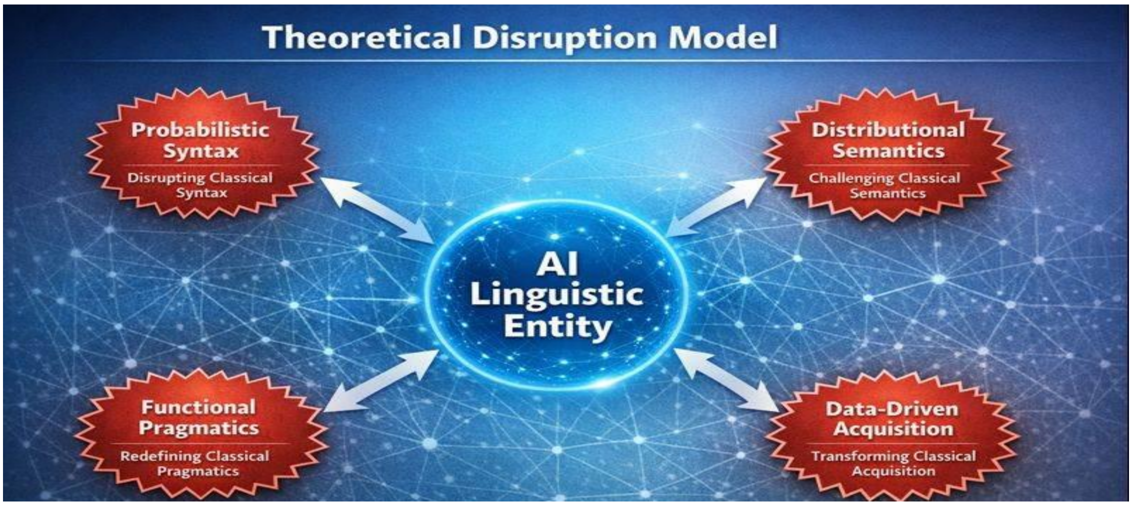
This paper discusses whether AI-based language systems are just imitators of human language or independent linguistic systems with unique structural and functional properties. The results show that AI systems are non-human linguistic systems that have syntactic, semantic, pragmatic, and acquisition patterns that do not conform to classical linguistic assumptions. In contrast to human language, grammaticality in AI is probabilistic rather than hierarchical, which favors usage-based and emergentist perspectives (Lau et al., 2017; Yeole, 2024). This questions the generative grammar paradigm and proposes that grammatical acceptability can be understood as a continuum determined by statistical regularities rather than categorical universals (Cartwright & Brent, 1997; Roberts et al., 2023).

The theoretical boundaries are further extended using semantic representation in AI models. Unlike classical semantics, which is based on reference, intentionality, and truth conditions, AI systems produce coherent meanings through distributional similarity in embedding spaces (Carter, 2025; Poibeau, 2025b). These results are consistent with and extend distributional semantic models by showing that semantic functionality may be operationally effective without intentionality or experience (Auganbayeva et al., 2026; Duvaa et al., 2013; Riemer, 2016). This deviation in human-based semantics underscores the necessity for theories that can accommodate both referential and non-referential meaning constructions.

Conceptual shifts are also manifested in the pragmatic outcomes. AI systems can attain discourse coherence and context-sensitive responses without social intentions, which distinguishes pragmatic functionality from pragmatic competence (Corsetti, 2015; Ifantidou, 2014; Munk et al., 2024; Patamia et al., 2025; Schnell, 2017). These decoupling questions anthropocentric pragmatics models and indicates that contextually relevant behavior can be generated by algorithmic processes without human-like cognitive social processes. In terms of language acquisition, AI models learn linguistic competence through large-scale exposure and optimization rather than being constrained by inherent limitations (Auganbayeva et al., 2026; Milosevic et al., 2025). Although this process is data-intensive compared to human acquisition, it demonstrates that there are other ways to learn languages. These findings broaden language acquisition theory by demonstrating that competence may result from exposure-based optimization rather than predetermined cognitive processes, thereby complementing but not refuting nativist views (Cain, 2021; Engelbert, 2015).

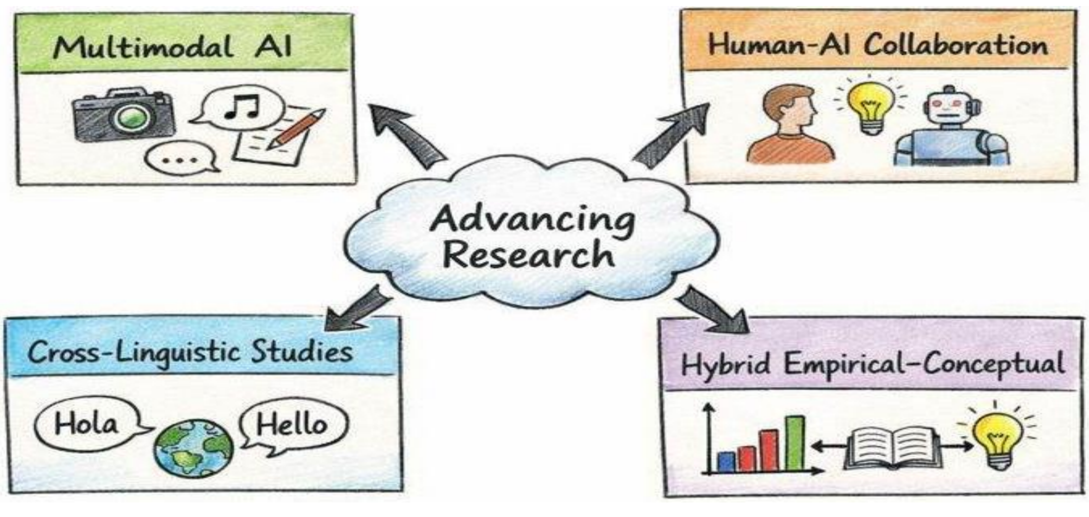
Together, these results make AI language systems legitimate objects of linguistic theory rather than tools for modeling human language. They challenge traditional assumptions, confirm elements of emergentist and distributional frameworks, and extend our understanding of grammar, meaning, pragmatics, and learning beyond human-centered constraints. Surprisingly, AI systems exhibited contextually consistent pragmatic behavior in the absence of intentionality, highlighting that human-like cognition is not always necessary for achieving functional linguistic performance. Future studies should examine how these non-human linguistic systems can inform AI interpretability and theoretical linguistics, thereby informing model design and sharpening our knowledge of language universals. In general, this paper advocates a pluralistic perspective on language, in which human and artificial systems are distinct yet structurally similar manifestations of linguistic competence (Bourguignon, 2023; Demuro & Gurney, 2023; Kwok, 2020; Zini & Awad, 2022). Figure 8 presents a model that explains how computational systems illuminate and disrupt classic frameworks in linguistic theory.

Figure 8
Linguistic Theory Adaptation Conceptual Model



Overall, the results indicate that AI-based language systems constitute a qualitatively distinct form of linguistic competence. They do not simply approximate human language; rather, they constitute other mechanisms of structure, meaning, and usage. This research advances a more comprehensive, theoretically sound conception of language in the era of artificial intelligence by recognizing these systems as independent language systems. Figure 9 shows possible future directions for research in computational language modeling, linguistic analysis, and interdisciplinary applications.

Figure 9
Future Perspectives of Language Modeling and Linguistic Study



Conclusion

This paper confirms that AI-based language systems are autonomous linguistic systems, and that their structural, semantic, and pragmatic characteristics are sufficiently distinct to challenge certain classical assumptions in linguistic theory. As shown in the analysis, syntactic organization is probabilistically developed, semantic coherence is developed in distributional representations regardless of referential grounding, and adaptation to context is developed without communicative purpose. The empirical acquisition routes also indicate that the emergence of complex linguistic competence is possible only after extensive exposure, thereby disengaging language learning from cognitive limitations. Taken together, the results reveal a hitherto unknown type of operational language competence, pointing to systematic deviations and alignments with human linguistic norms. Findings from this research offer a framework for re-evaluating grammaticality, meaning, and acquisition, both theoretically and practically, with implications for computational linguistics, cognitive science, and human-AI interaction. Although the study's conceptual-comparative design and use of literature published between 2010 and 2026 have certain limitations, it provides important critical standards for assessing AI language behavior. The emergent syntactic patterns require empirical testing in future research; multimodal semantic grounding warrants examination; and cross-linguistic generalizability should be evaluated. All these insights contribute to the development of knowledge of language as a structurally diverse, ontologically plural phenomenon.

Acknowledgement

The authors would like to express their sincere gratitude to their respective institutions for providing academic support and research resources. The authors also acknowledge the valuable contributions of the anonymous reviewers whose constructive feedback helped improve the quality and clarity of this manuscript.

Funding

This research received no external funding and was conducted without any specific grant from public, commercial, or not-for-profit funding agencies.

Use of Artificial Intelligence

The authors declare that artificial intelligence (AI) tools were used solely to assist with language editing, formatting, and improving the manuscript's clarity. AI was not used to generate original research content, data, or scientific conclusions. All intellectual contributions, analyses, and interpretations presented in this study are the sole responsibility of the authors.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper. There are no financial, personal, or professional relationships that could have influenced the research outcomes or interpretation of the findings.

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Journal of Ethnic and Cultural Studies
2026, Vol.13, No. 3, 382-410
http://dx.doi.org/10.66815/ejecs/3065

ISSN: 2149-1291

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