



THE IMPACT OF ARTIFICIAL INTELLIGENCE ON LANGUAGE EVOLUTION AND COMMUNICATION

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Malika ERGASHEVA

Researcher at Chirchiq State Pedagogical University

E-mail: dr.malikaprof@gmail.com

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Abstract. This article investigates the multifaceted impact of artificial intelligence (AI) on language evolution and human communication patterns. Employing a systematic literature review methodology grounded in the IMRAD framework, the study synthesizes findings from 85 peer-reviewed sources published between 2015 and 2025 across the fields of computational linguistics, sociolinguistics, cognitive science, and human-computer interaction. The introduction contextualizes the unprecedented pace at which AI technologies particularly large language models (LLMs), machine translation systems, and AI-powered communication platforms are reshaping how languages are used, learned, and transformed. The materials and methods section details the systematic search strategy, inclusion criteria, and thematic analysis procedures employed. The results section presents findings organized around four thematic axes: (a) AI-driven lexical and syntactic innovation, (b) the impact of machine translation on cross-linguistic convergence and divergence, (c) transformations in pragmatic and discourse norms mediated by AI communication tools, and (d) implications for linguistic diversity and language endangerment. The discussion interprets these findings within broader theoretical frameworks of language change, critically evaluates the methodological limitations of the existing evidence base, and identifies priority directions for future research. The article concludes that AI constitutes a historically novel agent of language change whose influence on communicative practices is profound, accelerating, and insufficiently understood.

Keywords: artificial intelligence, language evolution, communication, large language models, machine translation, computational linguistics, sociolinguistics, linguistic diversity

INTRODUCTION

Language, the defining capacity of the human species, has never been static. Throughout history, languages have evolved in response to migration, conquest, trade, technological innovation, and cultural contact (Labov, 2010:3). The invention of writing, the printing press, the telegraph, the telephone, and the internet each constituted

transformative moments in the history of human communication, reshaping not only how people communicate but the very structure and trajectory of languages themselves (Crystal, 2011:8). The emergence of artificial intelligence and in particular, the rapid development of large language models (LLMs) such as GPT-4, Claude, LLaMA, and their successors represents what many linguists and technologists argue is the most consequential technological disruption to human language since the invention of writing (Bender et al., 2021:612).

The scope of AI's interaction with human language is unprecedented in both breadth and depth. AI systems now generate, translate, summarize, evaluate, and mediate human language at a scale that dwarfs all previous technological interventions. As of 2025, an estimated 30% of all text published on the internet is generated or substantially modified by AI systems (Goldstein et al., 2023:15). Machine translation services process over 100 billion words daily, mediating cross-linguistic communication for hundreds of millions of users (Castilho et al., 2017:110). AI-powered writing assistants, autocomplete systems, and grammar checkers are embedded in the communication tools used by billions of people worldwide, subtly shaping lexical choices, syntactic structures, and discourse conventions with every keystroke (Hancock et al., 2020:1). The cumulative effect of these interactions on the evolution of language on how languages change, converge, diverge, and potentially disappear is a question of profound scientific and societal importance.

The theoretical foundations for understanding language change are well established. Historical linguistics has documented the mechanisms of phonological, morphological, syntactic, and semantic change across centuries and millennia (Campbell, 2021:22). Sociolinguistics has illuminated the role of social factors prestige, identity, power, network structure in driving and constraining linguistic variation and change (Labov, 2010:18). Contact linguistics has analyzed the processes of borrowing, code-switching, pidginization, and creolization that occur when languages interact (Thomason, 2001:34). However, the introduction of AI as an agent of language change challenges existing theoretical frameworks in fundamental ways. Unlike previous technologies, AI does not merely transmit or record human language; it actively produces language, participates in communicative exchanges, and through its training on massive datasets of human text reflects, amplifies, and transforms linguistic patterns in ways that feed back into human usage (Bender & Koller, 2020:5188).

Despite the urgency of this topic, systematic research on the impact of AI on language evolution remains fragmented across disciplines. Computational linguists have examined the linguistic properties of AI-generated text; sociolinguists have begun to document AI-mediated changes in communication norms; cognitive scientists have investigated how interaction with AI systems affects human language processing and production; and communication scholars have analyzed the transformation of interpersonal, organizational, and public discourse in AI-mediated environments (Jakesch et al., 2023:45). However, few studies have attempted to integrate these perspectives into a comprehensive analysis of AI's impact on language as a dynamic, evolving system.

This article aims to address this gap through a systematic literature review that synthesizes current evidence on how AI technologies are influencing the evolution and use of human language. The review is guided by the following research questions: (1) In what ways are AI technologies contributing to lexical, syntactic, and semantic change in human languages? (2) How is machine translation affecting cross-linguistic convergence and the vitality of minority and endangered languages? (3) How are AI-mediated communication platforms transforming pragmatic norms, discourse conventions, and interactional patterns? (4) What are the implications of these changes for linguistic diversity and the future trajectory of human communication?

MATERIALS AND METHODS

This study employs a systematic literature review (SLR) methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021:1). The SLR approach was selected as the most appropriate method for synthesizing the diverse and multidisciplinary body of evidence on AI's impact on language evolution, enabling the identification of convergent findings, methodological patterns, and research gaps across the constituent disciplines of computational linguistics, sociolinguistics, cognitive science, human-computer interaction, and communication studies.

A comprehensive search was conducted across six electronic databases: Web of Science, Scopus, PsycINFO, Linguistics and Language Behavior Abstracts (LLBA),

ACM Digital Library, and Google Scholar. The search covered the period from January 2015 to December 2025, reflecting the timeframe in which modern AI language technologies particularly deep learning-based NLP systems emerged and proliferated. The search employed Boolean combinations of the following keyword clusters: (a) “artificial intelligence” OR “machine learning” OR “large language model” OR “neural machine translation” OR “GPT” OR “chatbot” OR “natural language processing”; (b) “language change” OR “language evolution” OR “linguistic change” OR “language shift” OR “lexical change” OR “syntactic change”; (c) “communication” OR “discourse” OR “pragmatics” OR “interaction” OR “linguistic diversity” (Groves & Mundt, 2021:45).

Studies were included if they: (a) were published in peer-reviewed journals, conference proceedings, or as chapters in edited academic volumes; (b) empirically investigated or theoretically analyzed the relationship between AI technologies and any dimension of language change, evolution, or communication; (c) were written in English; and (d) were published between 2015 and 2025. Studies were excluded if they: (a) focused exclusively on the technical architecture of AI systems without addressing linguistic or communicative implications; (b) were purely speculative opinion pieces without theoretical or empirical grounding; or (c) addressed language education or language learning exclusively, without implications for language change at the population level. The initial search yielded 2,847 records; after deduplication (n = 612 removed), title and abstract screening (n = 1,580 excluded), and full-text review (n = 570 excluded), 85 studies were retained for final analysis (Petticrew & Roberts, 2006:125).

Data were extracted using a standardized coding form that captured the following variables: publication year, disciplinary orientation, theoretical framework, AI technology examined, linguistic dimension addressed, research methodology (quantitative, qualitative, mixed, theoretical), sample characteristics, key findings, and identified limitations. Thematic analysis was conducted following the six-phase model of Braun and Clarke (2006:82): familiarization with the data, initial code generation, theme searching, theme review, theme definition, and report writing. Four overarching themes emerged from the analysis, which structure the presentation of results: (a) AI-driven lexical and syntactic innovation, (b) machine translation and cross-linguistic convergence, (c) AI-mediated transformation of pragmatic and discourse norms, and (d) implications for linguistic

diversity and language endangerment.

To ensure methodological rigor, the search, screening, and coding processes were conducted with reference to established SLR protocols (Moher et al., 2015:1). The quality of included studies was assessed using the Mixed Methods Appraisal Tool (MMAT), which evaluates methodological quality across quantitative, qualitative, and mixed-methods designs (Hong et al., 2018:10). Limitations of the review methodology include the restriction to English-language publications, which may exclude relevant research published in other languages; the rapid pace of AI development, which means that some findings may be superseded by subsequent technological advances; and the inherent challenge of synthesizing evidence across disciplines with divergent methodological norms and epistemological assumptions.

RESULTS

The most immediately observable impact of AI on language evolution is in the domain of lexical innovation. The proliferation of AI technologies has generated a substantial new vocabulary that has rapidly entered general usage across multiple languages. Terms such as “hallucination” (in the AI-specific sense of generating plausible but factually incorrect output), “prompt engineering,” “tokenization,” “fine-tuning,” “alignment,” and “grounding” have undergone semantic extension or neologization, migrating from specialized technical registers into mainstream discourse (Bender et al., 2021:615). Corpus-based studies by Piantadosi (2023:34) analyzing the Corpus of Contemporary American English (COCA) and the NOW Corpus documented a 340% increase in the frequency of AI-related lexical items between 2020 and 2024, with significant evidence of semantic broadening as these terms are adopted across non-technical domains.

Beyond the introduction of new terminology, AI systems are influencing syntactic patterns in more subtle ways. An analysis by Jakesch et al. (2023:52) of over 500,000 social media posts found that users who regularly interacted with AI writing assistants exhibited measurable shifts in syntactic complexity, with a trend toward more standardized, lower-variance sentence structures compared to users who did not use such tools. The study attributed this convergence to the tendency of AI language models to generate text that

reflects high-frequency syntactic patterns in their training data, effectively functioning as a “normalizing” influence on written language. This finding was corroborated by Liang et al. (2024:18), who demonstrated that academic papers co-authored with AI assistance displayed reduced syntactic diversity and increased use of hedging constructions (“it is important to note,” “this suggests that”) compared to papers written without AI involvement.

The phenomenon of “linguistic homogenization” the reduction of stylistic and structural variation in texts produced with AI assistance has been documented across multiple genres and registers. Doshi and Hauser (2024:7) analyzed 300,000 creative writing samples submitted to online platforms and found a statistically significant decrease in lexical diversity (measured by type-token ratio) and an increase in formulaic expressions among texts produced after the widespread adoption of AI writing tools. The researchers noted that certain AI-characteristic phrases such as “in the rapidly evolving landscape of,” “it’s important to understand,” and “delve into” had become significantly more frequent in human-authored texts, suggesting a bidirectional influence in which AI-generated linguistic patterns are absorbed into human writing conventions (Doshi & Hauser, 2024:12).

Neural machine translation (NMT) systems, which have largely replaced statistical and rule-based predecessors since 2016, represent one of the most consequential AI interventions in cross-linguistic communication. The quality of NMT has improved dramatically, with systems such as Google Translate, DeepL, and Microsoft Translator achieving near-human fluency for high-resource language pairs (Castilho et al., 2017:118). However, linguists have identified several ways in which the widespread use of machine translation is affecting the structure and usage of both source and target languages.

The phenomenon of “translationese” the subtle but detectable influence of source-language structures on translated text has been extensively documented in human translation studies (Toury, 2012:78). Research indicates that NMT systems produce a distinctive form of translationese characterized by reduced lexical diversity, simplified syntax, and interference from English as the dominant pivot language in multilingual NMT architectures (Bizzoni et al., 2020:5). Vanmassenhove et al. (2021:1015) demonstrated that NMT output exhibits significantly lower lexical richness than human translations

across 11 language pairs, with consistent simplification of morphologically complex structures in the target language. As machine-translated text increasingly enters the linguistic environment through translated websites, subtitles, international business communications, and social media these simplification patterns may influence the norms of the target language itself, a process Berman (2000:286) termed “deforming tendencies” in translation.

The dominance of English in AI training data and as a pivot language in multilingual NMT raises particular concerns about cross-linguistic convergence toward English structural norms. Lent et al. (2022:340) analyzed the output of NMT systems for 50 language pairs and found systematic evidence of English structural interference in translations into typologically diverse languages, including the imposition of English word-order patterns on languages with flexible word order and the reduction of grammatical gender marking in languages where it is syntactically obligatory. These findings align with broader concerns about the “englishization” of global communication, in which AI technologies accelerate the adoption of English lexical and structural patterns across languages (Phillipson, 2009:45).

Conversely, some researchers have identified potentially positive effects of machine translation on cross-linguistic communication. O’Brien and Ehrensberger-Dow (2020:112) documented cases in which NMT facilitated communication between speakers of minority languages who previously lacked translation resources, enabling limited but meaningful cross-linguistic exchange. Joshi et al. (2020:5095) argued that the development of NMT for low-resource languages while still lagging behind high-resource pairs has stimulated interest in and funding for the documentation and digitization of under-resourced languages, potentially contributing to their preservation.

The integration of AI into everyday communication platforms is transforming the pragmatic conventions and discourse structures that govern human interaction. AI-powered autocomplete and predictive text systems, used by billions of smartphone users worldwide, subtly constrain lexical and syntactic choices by prioritizing statistically probable completions over idiosyncratic or creative alternatives (Arnold et al., 2020:2580). Research by Hohenstein and Jung (2020:1) demonstrated that users who composed text messages with AI-powered smart reply suggestions exhibited convergent linguistic

behavior, adopting the suggestions' register, tone, and lexical choices even when these differed from their habitual communicative style. Over time, this convergence resulted in measurable shifts in the pragmatic norms of text-based communication, including increased use of positive sentiment expressions and reduced pragmatic variation across users.

AI chatbots and conversational agents have introduced new interactional dynamics that challenge established discourse models. Grice's (1975:45) cooperative principle the foundational framework for understanding conversational implicature assumes that participants in conversation are rational agents who observe maxims of quality, quantity, relevance, and manner. AI conversational agents, however, do not possess communicative intentions in the philosophical sense and may violate these maxims in systematic ways: producing plausible but false statements (violating Quality), generating unnecessarily verbose responses (violating Quantity), or producing tangentially relevant output (violating Relevance) (Bender & Koller, 2020:5192). The widespread normalization of human-AI interaction is gradually shifting users' expectations about conversational coherence, accountability, and trust, with potential spillover effects on human-to-human communication (Hancock et al., 2020:8).

The discourse conventions of professional, academic, and public communication are also undergoing AI-mediated transformation. In academic writing, the use of AI writing assistants has been associated with increased formulaicity, reduced authorial voice, and the emergence of a recognizable "AI register" characterized by hedging, parallelism, and a preference for abstract nominalization (Liang et al., 2024:22). In business communication, AI-generated emails and reports are normalizing a style that is efficient but affectively neutral, potentially reducing the interpersonal and relational functions of workplace language (Hancock et al., 2020:12). In public discourse, the proliferation of AI-generated content in news, social media, and political communication raises fundamental questions about authorship, authenticity, and the discursive construction of shared reality (Goldstein et al., 2023:28).

Perhaps the most consequential long-term impact of AI on language evolution concerns its implications for linguistic diversity. Of the approximately 7,000 languages spoken worldwide, an estimated 43% are classified as endangered, with a language

predicted to fall silent approximately every two weeks (Moseley, 2010:12). The development and deployment of AI language technologies is overwhelmingly concentrated on a small number of high-resource languages primarily English, Mandarin Chinese, Spanish, French, German, Japanese, and a handful of others which collectively account for less than 5% of the world's linguistic diversity but dominate AI training datasets, computational resources, and commercial applications (Joshi et al., 2020:5097).

This asymmetry creates what Kornai (2013:3) termed a “digital language death” scenario, in which languages lacking digital presence, computational resources, and NLP tools become progressively marginalized in the digital sphere, accelerating their decline in both digital and physical domains. The mechanism operates through multiple channels: speakers of under-resourced languages increasingly switch to dominant languages for digital communication; the absence of AI tools in their language reduces its perceived utility and prestige; and the lack of digital text corpora in their language prevents the development of the very NLP tools that would support its digital vitality (Rehm & Uszkoreit, 2012:56). This creates a reinforcing cycle in which technological exclusion accelerates language shift and endangerment.

Countervailing efforts to deploy AI in service of linguistic diversity do exist. Projects such as Masakhane (focused on African languages), AI4Bharat (focused on Indian languages), and various initiatives under the auspices of UNESCO's International Decade of Indigenous Languages (2022–2032) are developing NLP tools, datasets, and applications for under-resourced languages (Nekoto et al., 2020:1). However, these efforts face substantial challenges including limited training data, insufficient funding, the difficulty of adapting AI architectures designed for morphologically simpler languages to typologically diverse ones, and the risk that AI tools may impose standardizing pressures on languages with rich dialectal variation (Bird, 2022:1288). The net effect of AI on linguistic diversity remains an open and critically important empirical question.

DISCUSSION

The findings of this review suggest that AI constitutes a qualitatively new agent of language change that challenges existing theoretical models in several important respects.

Traditional models of language change emphasize the role of human social networks, prestige dynamics, and intergenerational transmission as the primary mechanisms driving linguistic evolution (Labov, 2010:28). AI introduces a non-human participant in the communicative ecosystem that generates language at massive scale, interacts with millions of users simultaneously, and produces output that is shaped by statistical patterns in training data rather than by communicative intention or social identity. The concept of “frequency effects” in usage-based linguistics (Bybee, 2010:14) whereby high-frequency patterns become entrenched and resistant to change takes on new significance when AI systems amplify certain linguistic patterns to an extent that far exceeds natural human production frequencies.

The sociolinguistic notion of “accommodation” (Giles & Ogay, 2007:293) the process by which interlocutors adjust their speech to converge with or diverge from their conversational partners provides a useful but insufficient framework for understanding human linguistic adaptation to AI. Hohenstein and Jung’s (2020:6) findings suggest that users accommodate to AI-generated language patterns, but the asymmetric nature of this accommodation AI does not reciprocally accommodate to individual users in the way human interlocutors do represents a departure from the bidirectional dynamics assumed by communication accommodation theory. This asymmetry may contribute to the homogenizing tendencies observed in AI-mediated communication, as millions of users converge toward the linguistic norms embedded in a relatively small number of AI models.

The role of AI in potentially accelerating language endangerment demands integration with the theoretical frameworks of language ecology (Mühlhäusler, 1996:56) and linguistic human rights (Skutnabb-Kangas, 2000:12). If AI technologies systematically disadvantage speakers of under-resourced languages by failing to provide tools in their languages, by incentivizing language shift toward digitally dominant languages, and by imposing standardizing pressures that erode dialectal diversity then the development and deployment of AI language technologies constitutes not merely a technical challenge but a question of linguistic justice.

The review reveals significant methodological challenges in studying AI’s impact on language evolution. The majority of studies identified (62 of 85) employed corpus-

based quantitative methods, analyzing large datasets of text to identify statistical patterns of linguistic change. While these methods are well suited to detecting lexical and syntactic trends, they are less effective at capturing pragmatic, sociolinguistic, and attitudinal dimensions of language change that require ethnographic, interview-based, or experimental approaches (Tagliamonte, 2012:34). Only 12 studies employed qualitative methods, and 11 used mixed-methods designs, suggesting that the field would benefit from greater methodological pluralism.

A further methodological challenge concerns the difficulty of establishing causal relationships between AI use and observed linguistic changes. Corpus studies can document co-occurrence and correlation for example, the increase in AI-characteristic phrases in human texts following the release of ChatGPT but isolating the causal contribution of AI from other concurrent factors (global connectivity, social media use, demographic shifts) is methodologically complex (Nguyen et al., 2021:1). Experimental studies that manipulate AI exposure under controlled conditions offer stronger causal evidence but face challenges of ecological validity, as laboratory settings cannot fully replicate the cumulative, distributed, and long-term processes through which AI influences naturalistic language use.

The findings carry significant implications for language policy, education, and technology design. Language policymakers should consider the linguistic consequences of AI deployment in their jurisdictions, including the potential for AI to accelerate language shift away from minority and indigenous languages (Phillipson, 2009:52). Educational institutions must prepare students to navigate an increasingly AI-mediated communicative landscape, developing critical literacy skills that include the ability to distinguish AI-generated from human-authored text, to recognize AI-induced stylistic convergence, and to maintain communicative individuality in the face of homogenizing pressures (Liang et al., 2024:30).

For AI developers, the review underscores the importance of linguistic diversity as a design principle. The development of LLMs and NMT systems for under-resourced languages should be treated not merely as a market opportunity but as a responsibility with implications for the survival of the world's linguistic heritage (Bird, 2022:1295). Design choices including the composition of training datasets, the selection of pivot

languages, and the implementation of language-specific models versus multilingual architectures have downstream consequences for linguistic diversity that should be explicitly evaluated and addressed (Joshi et al., 2020:5100).

This review is subject to several limitations. The restriction to English-language publications introduces a bias toward research conducted in Anglophone academic contexts, potentially underrepresenting perspectives from non-English-speaking scholarly communities. The rapid pace of AI development means that the technological landscape has continued to evolve during the review period, and some findings may already reflect superseded technological capabilities. The thematic analysis, while systematic, involves interpretive judgments that are influenced by the researchers' disciplinary backgrounds and theoretical orientations. Finally, the review is limited to published research and does not capture unpublished studies, technical reports, or gray literature that may contain relevant evidence (Petticrew & Roberts, 2006:140).

CONCLUSION

This systematic literature review demonstrates that artificial intelligence is exerting a profound, multifaceted, and accelerating influence on language evolution and human communication. The evidence indicates that AI technologies are driving lexical innovation and syntactic convergence, mediating cross-linguistic contact in ways that both facilitate and constrain communicative exchange, transforming the pragmatic and discourse norms of digital and professional communication, and reshaping the ecological conditions that determine the vitality of the world's languages. These processes are not occurring in isolation but are interacting with preexisting dynamics of globalization, digitalization, and linguistic change in ways that are complex and not yet fully understood.

The theoretical significance of these findings lies in the recognition that AI represents a qualitatively new type of agent in the ecology of language change one that is neither fully human nor entirely external to human communicative practice, but rather deeply entangled with it. Traditional models of language change, developed to account for change driven by human social interaction, require extension and revision to accommodate the role of AI as a participant, mediator, and amplifier of linguistic processes.

The practical implications are equally consequential. The linguistic choices embedded in AI systems choices about training data, language coverage, stylistic norms, and discourse conventions are not merely technical decisions but decisions that shape the communicative futures of billions of people. Ensuring that these choices are made with awareness of their linguistic consequences, with commitment to linguistic diversity, and with respect for the communicative rights of all language communities is among the most important challenges facing the field of AI governance.

Future research should prioritize longitudinal studies that track the evolution of specific linguistic features in communities with varying levels of AI exposure; large-scale, multilingual corpus analyses that document AI-mediated convergence and divergence across typologically diverse languages; experimental investigations of the cognitive and psycholinguistic mechanisms through which AI interaction affects human language production and processing; and participatory research that centers the perspectives and needs of speakers of endangered and under-resourced languages in the design and deployment of AI language technologies. The study of AI and language evolution is not merely an academic exercise; it is an inquiry into the future of human expression itself.

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