The Neurolinguistics of AI: How Machine Learning Models Influence Human Language Processing

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Abstract

The rapid development of large-scale language models (LLMs) such as ChatGPT, Gemini, and Claudeover the past three years obliges not only to revolutionise the way language isdesigned and assigned, but also to revolutionise the way that human beings interact, learn, and exist with it. Although most experiments on artificial intelligence have focused on computational efficacy and natural-language processing, there is an urgent need to evaluate these systems within a neurolinguistic paradigm.This chapter explores how in-progress use of AI systems influences the human brain's processing of language—shaping its comprehension, usage and acquisition.

This chapter builds on prior discussions drawn from experiences gained by Levelt with his model of speech production, Kutas and Federmeier's work on speech processing (N400- an ERP - semantic processing), and Baddeley's theory of working memory. The study corroborates whether a long-term exposure to artificial systems converts lexical search, sentence-level understanding, word sense disambiguation, and monitoring complex discourse. At the same time, emphasis is given on multimodal AI interfaces, which concurrently show text, speech, and visual information, and their influence on cognitive load, dual coding, and memory consolidation.

Methodologically, psycholinguistics, cognitive neuroscience, and human-computer interaction data have been consolidated to suggest experimental protocols using event-related potentials, reaction-time paradigms, and comprehension tasks in comparisons between language produced

by AI and by humans. Real-life situations used in the study and analysisof case studies include ESL/ EFL learning, communications at the workplace and creative writing. The conclusion includes a focus on the idea that AI should not be perceived as an inert linguistic tool but as an intelligent language partner that has the potential to affect the process of learning language, promote linguistic standardisation, and facilitate neural efficiency. The chapter offers theoretical, pedagogical, and ethical propositions and considerations that linguists, educators, and technologists should consider when facing the changing nature of AI-mediated communication.

Keywords: Neurolinguistics, Artificial Intelligence, Machine Learning, Language Processing, Cognitive Neuroscience, NLP, Human-Computer Interaction

1. Introduction

Over the last decade, artificial intelligence (AI) has moved on to become a standard aspect of the communicative activity of millions, through the continuous implementation of AI into specialised laboratory research. With the recent success of so-called large language models (LLMs) (most notably OpenAI-initiated GPT sequences, Google-developed Gemini, and Anthropic-launched Claude), emails can be composed, texts translated, reports written, and a continuous conversation maintained with a deceptive semblance of the human-like conversationalists (Bubeck et al., 2023; OpenAI, 2023). These systems are not just a depository of language, but one that makes the best guess of the most likely continuation of linguistic context in any given way, making use of statistical regularities on a scale of billions of words.

The linguistic incorporation of AI has never been conducted at the scale or the pace before, which is why it demands investigation at both border levels and outside multiple fields, such as computer science, ethics, linguistics and cognitive science. Though it is an essential initiativeto analyse the inner workings of AI systems, it can be proposed that a potentially more pressing issue is to map how the interaction of humans and AI affect language processing in the human brain. The argument below is that this kind of engagement is by no means neutral; the neural networks that mediate language comprehension and production indeedrecalibratewith more time spent interacting with AI, and it affects the retrieval of lexical items, makes syntactic decisions, semantic associations, and discourse comprehension in measurable ways.

In the interdisciplinary field of neurolinguistics, researchers are hypothesisingconceptual frameworks and methodological approaches to examine the variations in language and the brain (Kemmerer, 2014; Stemmer & Whitaker, 2008). The neurolinguistic literature on classical neurolinguistics describes the spatial relationship between Broca, a region, Wernicke, a region, the angular gyrus, as well as other cortical and subcortical structures and comprehension, production and bilingual processing (Friederici, 2017). Much of repetitive work, however, has dealt with human-to-human or human and immutable text. Responsive and generative AI transforms linguistic input itself, that is, adaptive, multimodal, real-time and personalised to the user's linguistic profile.

This discussion makes two assertions. The former has to do with the linguistic implications of AI-mediated communication: through the generation of content maximised in order to facilitate clarity and coherence to users the world over, the communication in question generates speech patterns- syntactic, lexical, and discursive- not routinely evident in externally-created discourse. Such patterns can eventually naturalise certain syntactic forms and gradually put others on the periphery. The second argument targets the differentiating neurolinguistic outcomes of such an exposure, arguing that the effects of the latter do not evenly spread throughout the facets of proficiency, cognitive circumstances, and sociolinguistic backgrounds. Therefore, empirical studies and teaching strategies must be implemented to prove that the growing influence of AI on language application should not reduce but encourage linguistic diversity and cognitive strength.

The chapter places AI-human interaction in the intersection of computational linguistics, cognitive neuroscience and applied linguistics and states that it is a resourceful focal point of linguistic and cognitive change. The implications are far-reaching: having defined the neurolinguistic changes which accompany the AI, researchers and practitioners can make reasonable decisions regarding the possible benefits of AI to education, professional communication, and cultural preservation.

2. AI and the Neurolinguistic Architecture of Human Language(Theoretical Foundations)

This section defines theoretical principles of evaluating the neurolinguistic effects of AI. It assesses the neuroarchitecture of language, major psycholinguistic theories and notions of cognitive load and multimodal processing; at the same time, it compares them to those of AI.

Overall, these models support the idea that predictive plasticity of the brain makes it especially susceptible to being rewired as a result of interacting with AI-generated language over a significant amount of time.

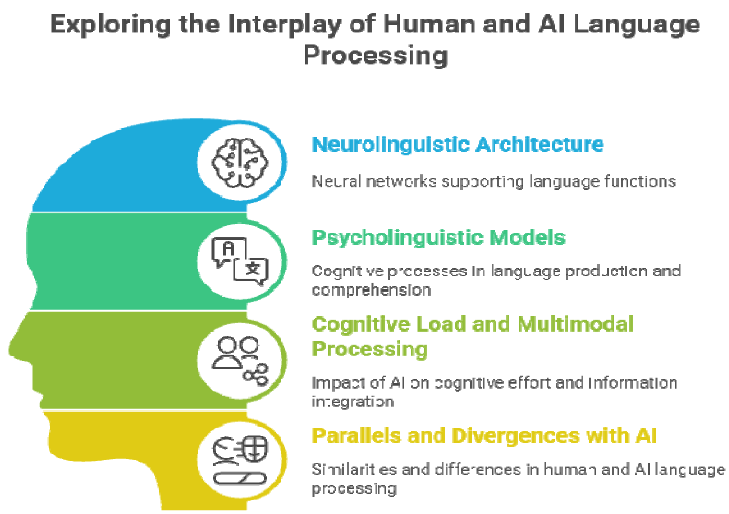

Figure 1. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

A critical review of the neurolinguistic implications of artificial intelligence requires putting machine-learning (ML) classes in the context of what is known of human language processing. Humans rely on a dispersed neural network: Broca facilitates morphosyntactic construction, Wernicke provides access to words and meaningful comprehension, and the arcuate fascicular system integrates acknowledgement and generation in real time (Hagoort, 2014; Binder et al., 2009; Catani & Bambini, 2014). More importantly, this network is predictive because ERP recordings show N400 reflects semantic system inconsistency and P600 of syntactic re-examination (Kutas &Federmeier, 2011). Transformer-based AI models also work on a probabilistic predictions principle, but through vector embeddings and self-attention instead of neurons (Vaswani et al., 2017), which explains why such models produce linguistic results that are aligned with the predictive logic of the human brain. This resonance implies that common exposure to AI can retrain predictive pathways, in ways that are never instinctively realised since the dominant cognitive processing of syntax and semantics will be subtly altered. As an illustration of this, when students have it drilled into them to use ChatGPT to write out essays, they may end up internalising its strong interest in what they call explicit cohesion and high-frequency syntactic frames, and these they then reproduce in their unassisted writing: a case that predictive exposure can influence the habituation of human production.

Empirical data indicate that the psycholinguistic theories support the idea that AI systems can rearrange communicative performance. A lexical retrieval process and working-memory demands rely on Levelt's (1989) tripartite schema of speech production, known as conceptualisation, formulation and articulation of the speech production tripartite schema (Baddeley, 2012). AI systems can reduce the cognitive load in making a selection between a set of lexical retrieval and the process of grammatical planning by supplying predictive options in lexical choice or syntactic templates. As a consequence, users do not need to have their cognitive resources as those associated with such stages are normally required. Although this type of scaffolding can hasten the processing, it can at the same time direct communicative output to frequently occurring AI-preferred syntactic constructions.

Similarly, models of comprehension, like the Construction-Integration model of Kintsch (1988), give pride of place to the inferential process; however, the tailoring of discourse by AI to maximal explicitness and coherence may prime the reader to anticipate maximal explicitness and coherence, thus weakening the inferential abilities that underlie deeper understanding. A good example can be given of the English-as-a-second-language learners who, after a long exposure to the AI feedback, end up continually using the formulaic sentence starters like the use of: *On the other hand…* offered by the system, thus limiting their selection as far as their stylistic collection goes.

Within the multimodal context, Cognitive Load Theory (Sweller, 1988) and Dual Coding Theory (Paivio, 1991) illustrate that actual presentation of verbal and visual information may be beneficial to learning since extraneous load occurs less frequently. As a result, AI interfaces with a combination of text, voice, and visual messages seem to be cognitively beneficial. However, overuse of this scaffolding can breed dependence because users will come to rely on the machine more and more when it comes to developing meaning-making tasks, as opposed to utilising their synthetic interpretive capabilities. Thus, what may be initially estimated as cognitive gain can, by plastic adaptation, reallocate neural effort patterns in such a way that, in the end, set to work less autonomous processing?

This conflict of facilitation and dependency is even more pronounced when the difference between artificial and human intelligence processing is looked at. In contrast to human cognition (where the meaning is rooted in embodied experience, Barsalou, 2008), AI is disembodied, and this approach takes precedence over statistical plausibility and understandability at a global level. Repeated encounters with such language could naturalisethe abstracting of discourse, rebuilding expectations of coherence balanced with machine-mediated standards rather than with human communicative variety. The presence of empirical evidence that can support the claim that repeated linguistic input may transform the neural architecture may be found in bilingualism (Li et al., 2014; Pliatsikas, 2020) and exposure to digital media (Small et al., 2009).

3. AI and Language Processing: The Computational Perspective

Based on the scaffolding of the theory of neurolinguistics and psycholinguistics, the discussion given below points towards how artificial intelligence manipulates language. Any argument about cognitive neurological consequences of language will have to be based upon the analogy between the processes that are accomplished by language and the processes that are accomplished by computational systems. Transformer language models, trained on large corpora, operate by statistical estimation, not by biologically explicit architecture, but their sensitivity to context, which requires latent representations, is similar to the predictive-coding process in the brain. This is a convergent observation indicating that frequent exposure to the discourse produced by the AI could rewire the way human's process information. The process of recalibration, however, is not because ofthe relationship between AI and cognition but because of the sense of algorithmic regularities, of new linguistic affordances in the environment to which the brain (in the plasticity of its organisation) responds.

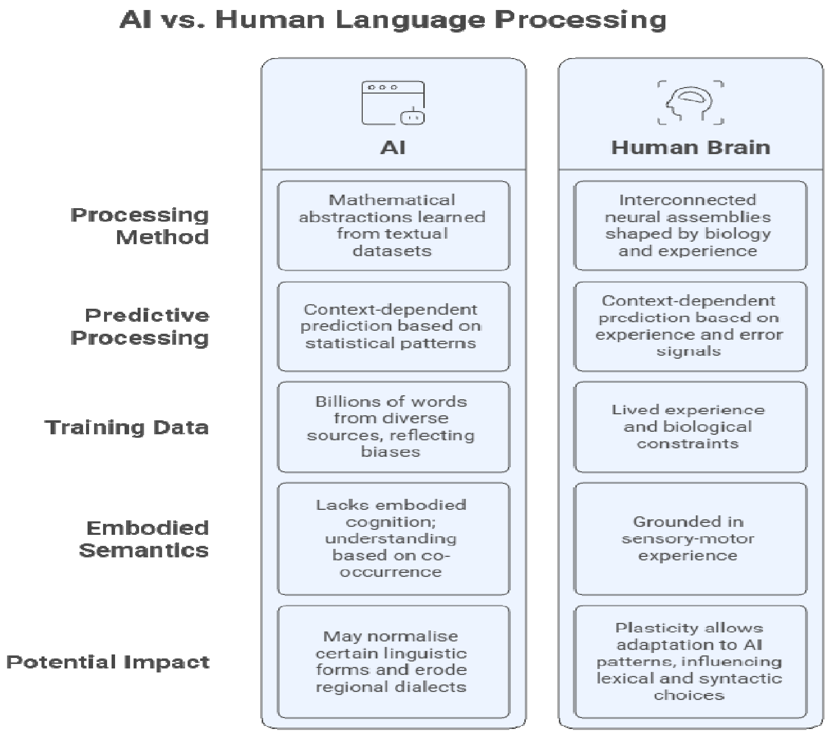

Figure 2. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

The neurolinguistics impact of AI systems should be the focus of systematic questioning, as computational strategies informing the linguistic embodiment adopted by the systems have a critical role to play in the interface between humans and digital language. The paradigm shift related to transformer architectures (Vaswani et al., 2017) can be found in the substitution of the strictly sequential processing with the self-attention networks that express long-range linguistic dependencies (transformer-based language modelling). Contextual cues are dynamically weighed, each token is encoded as a high-dimensional vector, and the predicted element is defined by the next element. Despite the striking differences between these computational mechanisms and biological neurons, their predictiveness bears a similarity with human predictive coding models, whereby the cortical networks constantly form predictions and update them using error feedback (Friston, 2010). The subsequent cognition is itself rather impressive: predictive text-primed learners tend to expect collocations traditionally scored by AI algorithms, like the tendency to write two consecutive words, a strong evidence pioneer and a strong indicator regressor. An analogous process can be involved in how users apply statistically entrenched biases in AI to their linguistic predictive repertoires.

The consequences of large-scale language modelling are noticeable in both the architectural planning dimensions as well as in the training set construction. As LLMs learn regularities applied to billions of words (Brown et al., 2020), such data sets also capture cultural and stylistic bias (Bender et al., 2021). In these circumstances arises a linguistic norm emphasises clarity and international intelligibility, giving precedence to mid-register standardised English at the expense of regional differentiation. The empirical results show that using ChatGPT to compose essays, ESL learners employ these standardised patterns, slowly substituting local idioms with standardised forms offered by artificial intelligence--a change that echoes sociolinguistic interests in linguistic convergence in mediated situations (Coupland, 2014).

Regardless of the growing situated ability of artificial intelligence (AI) systems, a visible gap can still be observed between the language performance of these systems and humans. Although linguistic perception has the effect of special-purpose neural networks in physical, sensorimotor regions of subjects (Pulvermuller, 2013), AI tends to interpret the meaning based on the statistical probabilities in the co-occurrence of lexemes and thus disregards the embodied referential functions which language mediates in human experiences (Barsalou, 2008). Further industrialisation of this kind of disembodied narrative production has the potential to diminish student-academic expectations of more complex narrative experience, where students will prioritise lexical over multimodal specificity to define narrative richness. There is an echo of this in the creative writing workshops where writers using AI-generated support often produce texts with smooth internal logic but little experiential depth, which again anticipates, and arguably exacerbates, the experiential vacuum of the core of AI-generated discourse.

The mappings that have been seen to appear in neural machine translation and computational language processing have shown that the brain is natively formative. The AI systems encourage high-frequency lexical choices that hasten retrieval and increasingly decontextualise less-often-used synonyms. Similarly, preferred syntactic patterns spread through priming processes that are similar to those reported in human conversation (Pickering & Ferreira, 2008). Moreover, artificial intelligence's contribution toward overt signalling encourages readers to require less inferential build-up throughout text and, therefore, has an impact on the way of thinking.

Therefore, the statistical nature of AI, its reliance on probabilistic forecasts and algorithmic optimisation, together with homogenised training datasets, is the means through which neurolinguistic effects are passed on. The computational detail at hand becomes a cognitive adaptation, discreetly re-tuning the perceptual and representational circuits of human language processing.

4. Hypothesised Neurolinguistic Impacts of AI

The human brain is an adaptive and plastic system predictive in nature and keeps changing according to the statistical properties of the linguistic environment (Pickering and Garrod 2013; Pulvermuller 2013). Integration of Artificial Intelligence (AI) as a standard communicative partner, therefore, does not appear as an amoral action but can be seen as a neurolinguistic change agent. The frequency-based and recency-based mediated lexical retrieval demonstrate that high-frequency words that have been exposed to other stimuli numerous times and whose neural representations are strong, need a shorter time to be called (Davis et al., 2009; Brysbaert et al., 2018). Since the clarity and accessible nature of AI-generated text are its priorities, this text employs words that are commonly used worldwide (Bender et al., 2021). These inclinations can make lexical access easier, particularly with second-language learners, but at the same time also pose a threat to lexical loss in that they weaken less frequently used synonyms.

A pedagogical explanation of ESL students making the point that persistent exposure to ChatGPT contracts their active vocabulary to those words which occur most often, a subtle but potentially significant alteration to their expressive repertoire, for example,using the word "*important"* rather than "*crucial" or "pivotal,"*. This trend also manifests itself in syntactic proficiency: neo-cortical areas like the Broca area (Friederici, 2017) offer a neural base for parsing, whereas the effect of syntactic priming, as described by Pickering and Ferreira (2008), indicates that recently retrieved syntaxes will be recycled in future speech and text. The tendency of ChatGPT to privilege more globally intelligible syntactic patterns can thus systematically direct the outputs of the user towards a more limited repertoire of syntactic patterns. Such recalibration is possible, but at the same time, it risks standardising style, which takes the form of the same sentence openings everywhere, like "*In conclusion*" or "*On the other hand"* in several essays.

The semantic processing is a dual phenomenon. Semantic priming records the strengthening of associative connections in the mental lexicon (Kutas and Federmeier, 2011), and more broadly trained artificial intelligence has the distinct advantage of favouring associations that are dominant, such as that between innovation and technology, as opposed to art or education. Such orientation is capable of enhancing creativity through exposure to new pairings, but can also create constriction in learners whose conceptual networks are still emergent, thus increasing associative homogeneity. Also, the bifurcated effect of AI is highlighted by discourse in comprehension. Signposted transitions and transparent summarisation are utilised to increase accessibility via optimised models in terms of explicit cohesion (OpenAI, 2023). This type of scaffolding can offload the learner, still at the L2, and those whose working memory is compromised (Sweller, 1988). Nonetheless, when viewing the informational space becomes heavily dependent on devices, the process of reasoning inherent in advanced literacy through inferential thinking and tacit coherence development can be suppressed (Graesser et al., 2011). The educational practice offers a typical example: when reading AI-generated summaries, learners can be seen to retain facts in evidence, but when faced with texts created by a human, they usually have difficulties in inferring the unstated implications.

Exploration of artificial intelligence (AI) production in natural language signals to a mode of production that is not the direct transcription of human language behaviourcharacterising production; it is more accurately seen as a re-articulation of such behaviour under an algorithmic register whose priority is an optimisation of frequency, clarity, and predictability. Given the inherent plasticity of human brain (Li et al., 2014; Pliatsikas, 2020), chronic exposure to AI-generated text is likely cause an increase in brain activation volume related to the recall of common words, use of common syntactic structures, and the reliance upon conspicuous cohesive techniques and, in turn, a decrease in the volume of brain activation that is related to the use of uncommon words, versatile syntactic forms, and lexical and semantic richness, and understanding of implicit aspects of the text. Here, the machine optimisation that underpins AI output forms the conveyor belt along which neurolinguistic adaptation is led, imprinting machine-desired linguistic forms on the predictive brain circuits of human cognition.

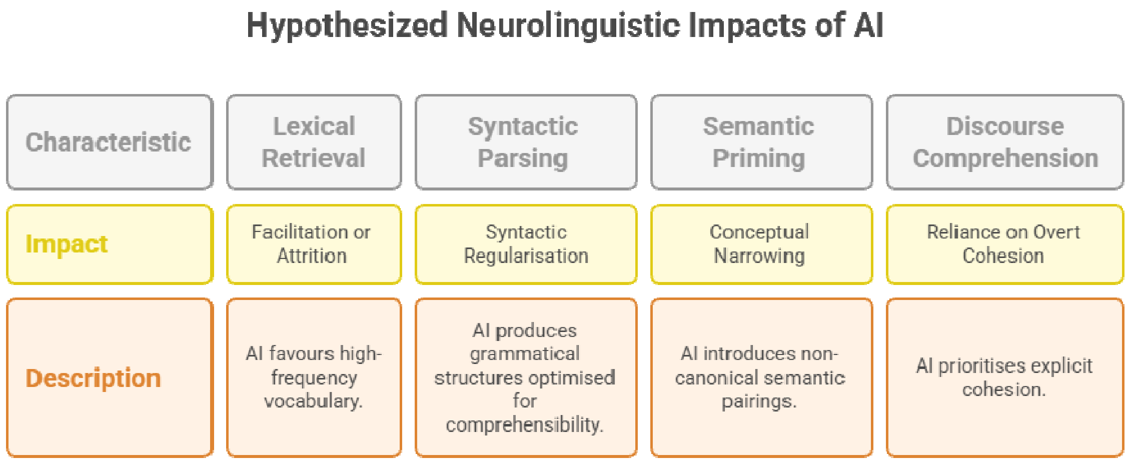

Figure 3. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

5. AI in Second Language Acquisition (SLA)

The belief is that second language acquisition (SLA) presents a privileged context in which to study the neurolinguistic implications of AI, as neural representations learning the target language are said to remain in a state of consolidation, and, thus, are more vulnerable to input-driven modification (Li et al., 2014; Paradis, 2009). Neuroimaging testimony proposes that, at lower stages of language, L2 learning demonstrates bilateral cortical recruitment together with right-hemisphere analogues of basic language territory, but, at superior capability, a continuing switch to left-lateralised blueprints reported in fundamental speech (Perani and Abutalebi, 2015). This neurocognitive reorganising has already testified to the plasticity of the brain, but at the same time, this fact also highlights the fact that, where AI contributes a sizeable part of the linguistic environment, its defining characteristics, the lexical frequency distributions, syntactic regularities and discourse explicitness, are imbibed in the developing neural network. Thereby, AI will not only be a neutral tutor but also a strong influencer of the linguistic circuits, which are beingbuilt.

The benefits of artificial intelligence concerning second language acquisition can also be confirmed: adaptive feedback systems allow correcting in real-time, which scaffolds learners into the zone of proximal development (Vygotsky, 1978; Godwin-Jones, 2021), and the presence of high-input environments at all times contributes to a greater frequency of exposure, which is positively related to proficiency (Ellis, 2002). Moreover, multimodal design stimulates the functioning of various cognitive pathways and, thus, aligns with Dual Coding Theory (Paivio, 1991). In neurolinguistic terms, these affordances are making lexical retrieval faster, automating syntax, and creating more precision in its understanding. An extreme example of this can be seen with L2 users of Duolingo or writing tutors like ChatGPT, whose corrections also on these grammatical features (the number of articles, prepositions etc. in an article or conjugation of the verb), often express themselves in more quick acquisition of specific forms, than those users who are instructed solely in a traditional classroom environment. There are, however, risks associated with these advantages: transformer-based language models, risk-optimised on clarity and geographical intelligibility, drift toward mid-range, uniformised English (Bender et al., 2021), whereby the resultant repertoire is both functional but also homogeneous, potentially lacking in local colour or local accentuation. This effect, which has already been observed in ESL literature wherein the ESL learners are over-exposed to AI-preferential lexical items, takes the form of using the AI-preferential terms higher than phrasal verbs like quit and investigate against give up and look into.

The current discussion reproduces the conclusions made by Schmid and Kopke (2017) in their study of input-induced attrition, where prolonged use of lesser forms of input eventually makes them fall below infrequent use. The increased use of AI-facilitated language contact can come in the form of a decreased ability of learners to use colloquial speech, local forms of the language and culture-specific metaphors, which limits communicative agility. Moreover, the presence of permanent lexical and syntactic scaffolding that AI systems provide has the potential to foster cognitive dependency as a cognitively offloading-related effect identified by Risko and Gilbert (2016) that reduces problem-solving engagement in learners. In theoretical terms (SLA), this cognitive dependency hinders the implementation of procedural memory systems that play an important role in fluent and spontaneous production, as stated by Paradis (2009). A practical pedagogical example of such phenomenon can be seen in the case of conversation classes: in students who have been at least partially sedated by AI-guided training, it is not uncommon to have problems with written grammar problems and then completely fail in the live conversation, where they begin to interrupt speech, looking, so to speak, at the "*syntactic trees*" provided by the AI, and picking up resources in language classes with little or no activity at all.

The effectiveness of artificial intelligence (AI) in SLA is admittedly a matter of a combination of both cost efficiency and ability to provide consistent input, with the possible drawback of excessive standardisation: the duality of AI. Optimised and consistent input, but also the risk of human homogeneity created by AI.

1. The initial educational agenda is to complement AI-produced content with the material developed by humans and comprised of various registers and dialects.

2. Automatically generated recommendations shall be taught to be reviewed critically by learners. 3. They can alternate AI-aided tasks with AI-free activities, therefore maintaining self-generative input.

Conclusively, AI shows potential to greatly accelerate SLA due to its adaptive, multimodal, and ample input, although without pedagogical governance, the result could be learners who are simultaneously proficient and monolithic to the detriment of the linguistic diversity neurocognitively enabled.

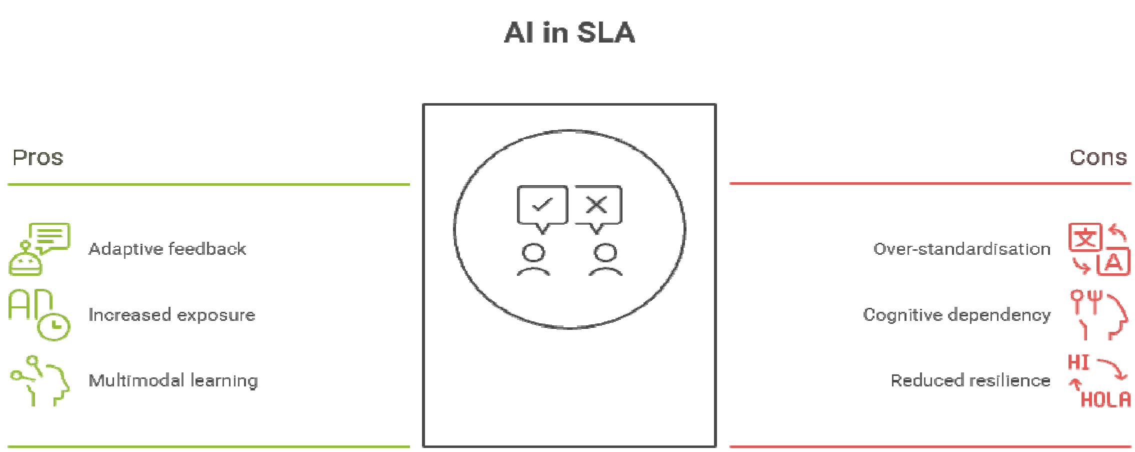

Figure 4. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

6. Potential Cognitive Shifts

The addition of artificial intelligence (AI) to daily communication cannot be easily disregarded as a mere technological improvement, thus signalling a possible cognitive turning point. Conventional models of language processing have highlighted its plasticity and predictive qualities, which make the human language extremely situational to the type of scaffold that AI can provide. One of the fundamental issues in this regard is that of cognitive offloading: whereas external aids can potentially reduce the associated strain on internal processing resources and transfer them to higher-order thinking (Risko & Gilbert, 2016), excessive use exposes one to the risk of losing the neural connections that help them access the lexicon and produce syntax. Neuroimaging evidence suggests that repetitive learning enhances functional connectivity between temporal and frontal cortices, but in the case of AI always suggests words to choose or leads to reformulating sentences, theusers become less capable of using these circuits, reducing neural efficiency in the domain of being less dependent on help. This paradox can already be seen in classrooms where students who grew up using AI-based drafting tools write fluently and, when performing their quick oral presentations, stop and struggle to access forms that they previously used as a scaffold with AI. A second turn is apparent, what one might call the algorithmic echo effect: given that in large language models (LLMs) optimisation aims at coherence by replicating common constructions (Bender et al., 2021), the preferred syntax and vocabulary blanks are reinforced through uptake by users.

In Syntactic priming studies (Pickering & Ferreira, 2008), lexical repetition is more likely, having been previously encountered, and this concept can be used to naturalise structural biases in automated language models (Eagle et al., 2020). In the realm of customer service, e.g., chat support made capable with AI encourages an agent to adopt formulaic expressions as "*We appreciate your patience*" and/or "*Thank you for reaching out*", undermining the stylistic diversity that has in previous centuries characterised human-human communication. The sociolinguistic implications of these developments are that, since the main task underlying the training of AI systems is done using standardised corpora, there is a trend in which AI systems overlook dialectal markers, idiomatic expressions, and culturally applicable metaphors (Bird, 2020). Learners who rely more on this kind of input, especially L2 language learners, risk developing communicative competence that is culturally limited though functionally competent and this is something that people have long feared about broadcast media and globalised educative space (Coupland, 2014).

Neurolinguistically, limited exposure to the diversity of registers limits the flexibility of the neural circuitry underlying code-switching and the pragmatic adaptation (Green &Abutalebi, 2013). In all these scenarios, the use of artificial intelligence (AI) contributes to the reproduction not only of communication but also to a rerouting of the work of linguistic organisation in the form of prioritising high-frequency norms and relegating dialectical variation to the background. In this way, by shaping the input to which the predictive neural systems should adjust, AI becomes a homogenising force, to which individual mental processes are changing, and a communal linguistic ecology is changing as well. As a result, integration of AI is not the primary task, but creating a balance between affordances and motivated pedagogical and cultural efforts with the view to preserving the richness and flexibility of human language.

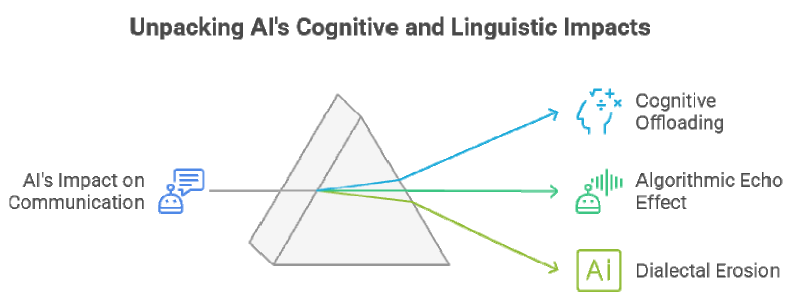

Figure 5. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

7. Proposed Experimental Frameworks

Despite the fact that the theoretical language of thought and the analogical reasoning between AI technologies and the human mind point to the possibility of neurolinguistic implications, the empirical validation is of unsurpassable importance. Experimental design is possible to answer the question of whether AI-mediated communication moderates lexical retrieval, syntactic parsing, semantic priming and discourse comprehension. There is a plethora of methodological perspectives that will enlighten these difficulties. An example of real-time measure generation is in an event-related potential (ERP) study, where N400 and P600 are obtained to determine semantic incongruity and syntactic reorganisation, respectively (Kutas &Federmeier, 2011). Analysis of neural reaction to sentences produced by AI, as compared to those made by humans, allows researchers to establish whether the stylistic characteristics of AI-generated sets of words, such as explicit cohesion and simplification of syntax, diminish those responses, suggesting a lower semantic demand, or affect syntactic involvement. In case repetition of exposure to AI summaries, say, systematically reduced N400 amplitudes during reading tasks, this finding indicates that the brain is learning to adapt to the statistical preferences of AI, through which simplifying task processing can come at the expense of flattening semantic awareness. As a complement to ERP results, eye-tracking will help to investigate the effects of the short sentences and overt transitions introduced in AI on the reading path. Less jagged patterns and fewer regressions might seem preliminarily beneficial, but can also point to lessin-depth involvement, such as when readers peruse AI-created study notes more effectively than the typed written textbooks, before being faced with increased difficulty later in remembering the subtle relationships in study notes (Rayner, 2009).

Further empirical evidence on the access of lexical and syntactic information is given by Reaction-Time (RT) paradigms. Improved recognition of high-frequency words after exposure to artificial intelligence (AI) adds evidence of facilitation, and slow recognition of idiomatic and low-frequency tokens adds support to the hypothesis of lexical narrowing (Balota& Chumbley, 1984). Another hypothetical experiment is priming AI-created contexts to theparticipants to present '*important*', '*pivotal*', and 'give *up*'. With faster recognition of *important,*it slows down therecognition of *pivotal*, and *gives up*, which reveals the potential of the AI to transform the lexical salience. Longitudinal designs play an important role in determining whether these changes are continuing. The evidence in the form of neuroplasticity research of dispositional neuroimaging studies shows that prolonged input leads to changes in connectivity and even density of grey matter in language-related cortical areas (Li et al., 2014; Pliatsikas, 2020). Six- to twelve-month monitoring of the native speakers, L2 learners, and bilinguals, heavily using AI, may allow measuring any modifications associated with the lexical diversity, syntactic range, comprehension strategy development, and adjusting the latter variables to the explicitness of AI. In addition, the possibility that these effects were different in terms of cultural contexts would also have to be critically controlled.

Most recent investigations to assess the neurolinguistic impact of artificial intelligence (AI) such interdisciplinary constellation of neurophysiological, behavioural and longitudinal methods have demonstrated that the effects are not exempt beyond empirical study, indeed, can be methodically observed and measured and therefore generate evidence, essential not just to further theoretical refinements but, equally to pedagogical advancement as well as the engineering of technological systems. Without such a practical basis, argumentation about the relevance of AI to language risksbeing speculative as it places educators, learners and societies at risk of cognitive shifts which occur silently.

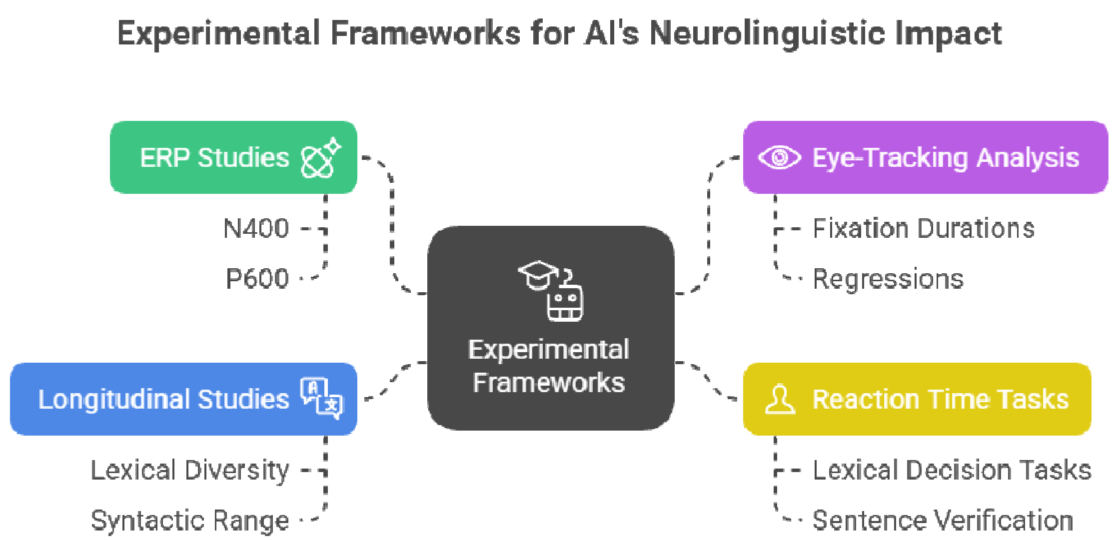

Figure 6. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

8. Ethical and Educational Implications

Given that AI can theoretically transform neurolinguistic processing, its impact goes well beyond theory into the fields of education, ethics and policy, necessitating a delicate balance between the capabilities of technology and human intellectual growth. The issue of overdependence: on the one hand, cognitive offloading can release cognitive resources to perform higher-order reasoning (Risko & Gilbert, 2016), but, on the other hand, over-relying on AI may lead to the degeneration of the neural pathways that are involved in the processes of retrieval, composition, and inferential thinking (Hsu et al., 2017). It is not only the question of lost skill but also freedom, as language is closely bound with identity and agency. As students write with high levels of scaffolding provided by AI, such as when creating complex essays, they might gain fluency in written text, but lose their ability to express thoughts in free dialogue, and this is why expressive outsourcing may lead to giving up authorial authority and expressive autonomy to machines. Inclusivity as a moral mandate is also smouldering.

The current generation of artificial intelligence largely learns with the use of standardised and globally distributed English, leaving low-resource languages and non-standard dialects in relatively marginal states (Bender et al., 2021; Bird, 2020). At a neurolinguistic level, this homogenisation confines access to linguistic diversity to the point that the brain capacity to cope with different input is compromised (Green &Abutalebi, 2013). A contrast of the rich expressiveness of Caribbean English Creole speech with the more level mid-register favoured by AI shows how the expressive richness of language can be disadvantaged by algorithmic design. Due to this, inclusive design is a cognitive necessity and ethical need, forcing the incorporation of corpora representing minority languages, regional variants, and multimodal discourse forms lem see treats. However, it is not just about the choice of inclusive corpora, but necessarily, a pedagogical mediation. There is a need to shift past the binary choice between prohibition and uncritical adoption and engage AI in terms of a diversity of input, critical literacy, AI-free assignments, and collaborative paradigms that would frame AI as a co-pilot but not a replacement (Gee, 2015; Floridi & Chiriatti, 2020). Practically, this could translate to the comparison of AI-generated articles and human-written ones, or the task of writing reflections that critique AI-recommended texts on bias and tone. These approaches maintain independent production strategies and develop metalinguistic awareness so that learners do not become inactive in the meaning-making process.

The analysis offered in this context highlights the fact that Artificial Intelligence (AI) does not have a fixed utilitarian, convenience-based purpose but is a dynamic agent that can limit expressive repertoires and stimulate dependency in case the mechanisms of governance are weak. With the corresponding design ideas and teaching-learning activities, however, AI may act as a custodian of linguistic fitness and a promoter of international communication. It would therefore be imperative to consider shunning the allure of mindless adoption to enable and incorporate the usage of such practices, which can assure protection to linguistic diversity, while safeguarding the cognitive integrity of the human mind.

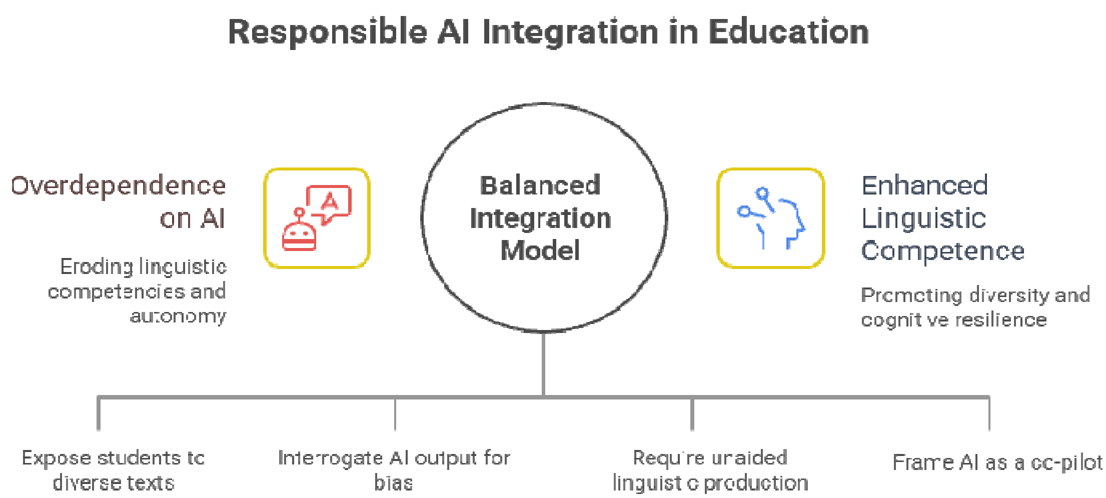

Figure 7. Conceptual diagram of language processing pathways. Generated with the assistance of Napkin AI (2025).

Conclusion

Artificial intelligence and large language models in particular are not mere neutral communicative tools but rather language-level machinists that have the potential to reorganise human neurolinguistic processes in terms of their lexical, syntactic, semantic, and discourse-level patterning. The human brain is highly predictive and plastic, which is the characterisation of the human brain which adjusts to the statistical consistency of the immediate environment (Pulvermuller, 2013). Since the language produced by AI becomes more and more persistent in these settings, the adaptations it causes in the brain are not incidental but more structural in that they reorganise how people access vocabulary, how they divide syntax, how they build semantic networks, and how they understand discourse.

This explanatory pathway opens with an illustration of the neurolinguistic underlying foundations of language, specifically, the Broca and Wernick regions, where predictive processing, as realised through event-related potential (ERP) measures, like N400 and P600, represents the available subdivisions, through which fluent communication flows (Friederici, 2017; Kutas &Federmeier, 2011). It is then compared with these biological systems to transformer-based AI architectures, with functional analogues identified in predictive processing but strong distinctions also emphasised with regard to the lack of embodied semantics (Barsalou, 2008; Vaswani et al., 2017).

The exposition in this chapter argues that repeated exposure to artificial intelligence causes an observable change in one linguistic behaviour: the access to the high-frequency lexicons is now optimised, whereas the access to less frequent forms is dampened (Brysbaert et al., 2018); the syntactic regularisation is encouraged because of the priming effects as well (Pickering & Ferreira, 2008); the semantic networks are clipped through biased co-occurrence patterns (Bender et al., 2021); the learners with adaptive scaffolding, the scale of these impacts is magnified even further in second-language acquisition, where AI-driven adaptive scaffolding accelerates the learning process but can also be the trigger of over-standardisation and cognitive dependence (Godwin-Jones, 2021; Risko & Gilbert, 2016).

Three noteworthy cognitive and sociolinguistic trends affirm academic concern: cognitive delegation, algorithmic echo effect and dialectical erosion. The delegation of linguistic processing onto artificial intelligence, that is, cognitive delegation, potentially undermines neural efficiency when people rely on external systems to be able to produce independently. Its algorithmic echo effect plays up on high-frequency patterns in place of the possible loss of stylistic variety. In the meantime, the copyrighting of world languages due to dialectal erosion involving a trend toward lingual homogeneity in dialogue of languages at the expense of a globalised English language is dangerously destroying plurilingual diversity. To provide empirical support for these statements, the present chapter suggests experimental designs that combine event-related potentials (ERP), eye-tracking, reaction-time tasks, and longitudinal designs (Li et al., 2014; Pliatsikas, 2020).

The moral and social implications of highly sophisticated artificial intelligence (AI) are huge. The absence of the crucial interventions makes AI serve to increase language staleness and the loss of control in a form of expression. However, under the condition of inclusive design achieved by using heterogeneous data corpora, and pedagogical practices based on balancing the

AI-supported and AI-free linguistic activity, AI could be used to expand the human linguistic ability, instead of limiting it (Floridi&Chiriatti, 2020). Then developers, educators and policymakers are accountable for making AI a partner and not a coloniser of the human linguistic mind.

Finally, the chapter argues that the field of neurolinguistics cannot afford to ignore AI. The interplay between human neural structure and paradigms of machinelearning is not some speculative sub-discipline of inquiry; it is a dynamic, bi-directional, and productive relational contact. Since AI is gaining ground in language practices, itinevitably has a non-neural and non-cultural imprint.

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