2026, Cilt 3, Sayı 4, 28-39

OPEN ACCESS

ISSN: 3062-262X

Akademik Eğitim ve Sosyal Bilimler Dergisi (AJESS Journal)

Prompt Engineering Techniques and the Generation of Cognitive Linguistic Hypotheses: A Cognitive-Computational Linguistic Approach

Dr. Hanane Mosbah, Batna 1 University - Hadj Lakhdar (Algeria), Department of Arabic Language and Language Sciences, Research Laboratory on Intellectual and Literary Heritage in Algeria (Batna - Algeria)
hanene.mosbah@univ-batna.dz

Article History
Received: 31/07/2025; Accepted: 22/08/2026; Published: 30/09/2026

Abstract:
This study uncovers the methodological and epistemological intersections inherent between Prompt Engineering techniques and Cognitive Linguistics, in light of Large Language Models (LLMs) as generative tools for linguistic hypotheses. The study stems from an epistemological problematic that attempts to monitor the extent to which engineered prompts can function as "semantic stimuli" capable of eliciting and simulating human cognitive structures—chief among them conceptual metaphors and image schemas established by George Lakoff and Mark Johnson—and employing them to generate robust and scientifically falsifiable cognitive linguistic hypotheses. The research paper posits that formulating input prompts based on specific cognitive frameworks (such as conceptual metaphor, mental spaces, and image schemas) enables intelligent systems to simulate human cognitive structures and generate high-precision explanatory hypotheses that mimic conceptual blending spaces. To implement this, a comparative method integrating cognitive computational linguistics and deep learning models was adopted to examine the mechanisms of transition from technical textual input to cognitive linguistic output. This highlights that "Prompt Engineering" is not merely a mute programming tool, but rather a "guided linguistic structure" that stimulates the latent semantic networks within the automated model. The study concludes by presenting an epistemological model that defines the efficiency and limits of automated generation compared to human cognitive analysis, while providing applied frameworks on how to harness the "prompt" as a generative tool in contemporary linguistic research.

Key words: Prompt Engineering; Cognitive Linguistics; Linguistic Hypotheses; Large Language Models (LLMs); Modeling Cognitive Processes; Artificial Intelligence.

Introduction:

The current intersection between cognitive sciences and artificial intelligence represents one of the most prominent features of the epistemological shift in modern linguistics. Large Language Models (LLMs) are no longer merely simple statistical tools for predicting the next word in a textual sequence; rather, they have become virtual computational environments capable of processing and producing highly complex semantic representations. In this regard, "Prompt Engineering" emerges as a crucial link, through which the machine is guided to elicit texts and extract the latent cognitive patterns within them. This study is of paramount importance given our urgent need to bridge the gap between purely computational techniques and cognitive linguistic theories. We investigate how to transform prompt formulation from a mere technical practice following software engineering into a generative methodological tool that contributes to formulating robust scientific hypotheses about how the human mind and language operate.

Among the contemporary methodological challenges facing cognitive linguistics today is the issue of how to model and explain complex mental processes (such as conceptual blending, framing, and metaphorical analysis) and how to apply them to massive amounts of textual data generated in the digital age through prompt engineering techniques as a tool to control and computationally guide the outputs of these models. Hence, the research problematic crystallizes in the following pivotal question:

How can prompt engineering techniques be invested as a methodological mechanism to produce and generate cognitive linguistic hypotheses characterized by accuracy, explanatory depth, and alignment with human mental structures without falling into the trap of machine hallucination?

A set of sub-questions branches out from this problematic, most notably:

1. What is meant by prompt technology or prompt engineering, the generation of cognitive linguistic hypotheses, and Large Language Models (LLMs)?
2. Is there a cognitive concept of artificial intelligence through which we can draw a parallel between human cognition and machine learning?
3. How does the linguist guide the machine to produce cognitive linguistic hypotheses?
4. What is the maximum limit that the machine reaches when analyzing hypotheses using artificial intelligence that allows it to surpass human capability in studying semantic memory?
5. What are the epistemological challenges facing the machine, such as linguistic hallucination and the absence of embodiment?

Hypothesis:

The study stems from a main hypothesis stating that:

"The efficiency of large language models in generating coherent cognitive linguistic hypotheses is directly proportional to the extent to which prompt engineering is infused with theoretical frameworks and contextual cues derived directly from human cognitive mechanisms (such as embodiment, spaces, and metaphorical mappings). Meaning: the more precise and controlled the input commands (prompts) are, the more we stimulate artificial intelligence to generate large language models that simulate the capacity of human cognition to represent conceptual metaphors, possible spaces, and conceptual blending. Accordingly, the cognitively designed prompt does not function as a dry technical command, but rather as an activation structure that stimulates artificial intelligence to reproduce complex semantic relations mimicking human mental spaces, which reduces generative deviation 'cognitive hallucination' and increases the scientific value of the generated hypotheses."

First: Artificial Intelligence (Its Concept and Operating Tools):

1. Concept of Artificial Intelligence (AI): The Saudi Data and AI Authority defined the boundary of the term as a scientific and engineering field aimed at innovating intelligent systems and machines capable of simulating human cognitive abilities, and performing complex tasks that require learning, reasoning, and problem-solving (Saudi Data and AI Authority [SDAIA], 2024, p. 05). The history of integrating artificial intelligence technologies into educational systems spans several decades, during which it passed through four pivotal phases:

- **The phase of natural language processing and the development of rule-based systems (1960–1974):** Among its most prominent milestones was the appearance of the "ELIZA" program in 1966 as a prototype for conversational simulation. Afterwards, the "SCHOLAR" system was developed in 1970, which was dedicated to posing interactive questions about the geography of South America and providing immediate feedback; it is historically classified as the first Intelligent Tutoring System (ITS).
- **The phase of developing expert systems (1975–1990) "Expert Systems":** Among the most famous was the "MYCIN" medical system for diagnosing bacterial infections, which laid the structural building blocks for knowledge modeling in contemporary Intelligent Tutoring Systems. This phase also witnessed the scientific institutionalization of this field through the publication of the first issue of the "International Journal of Artificial Intelligence in Education" (IJAIED).
- **The phase of the proliferation of e-learning and distance education (1990–2010):** This coincided with leaps in machine learning (ML) algorithms and natural language processing (NLP), which contributed to upgrading human-machine interaction, and deploying artificial intelligence on a large scale in automated and intelligent assessment systems, particularly in the field of foreign language acquisition.
- **The phase of the deep learning revolution "Deep Learning" (2010–Present):** In this phase, Generative AI technologies emerged, and generative models diversified to include Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models specialized in generating images and media (Barkah Meshnan, Iman Ben Kessir, 2025, p. 237).

2. Concept of Generative Artificial Intelligence (Generative AI): Generative artificial intelligence is defined as "an advanced generation of intelligent systems and software that are not limited to simulating human intelligence for data collection and performance enhancement, but possess the capacity to innovate and create entirely new content (texts, images, or media) based on the data they were trained on, as the forms and applications of this technology diversify within contemporary digital environments" (Amira Nasser Al-Qahtani, 2025, p. 9).

Generative AI (GenAI) also represents an advanced technology that employs artificial intelligence algorithms to create new and innovative content. This technology is utilized across a wide range of applications and use cases where the user interacts with the generative machine via natural language conversational interfaces to obtain immediate responses. Instead of being restricted to indexing texts to organize existing web pages, language models possess the ability to generate texts, images, and all representative symbols of human thought. This diversity extends to include photographs, digital paintings, animations, video clips, and musical pieces, in addition to software and computing codes. Generative artificial intelligence systems are trained relying on massive amounts of data collected from web pages, social media platform conversations, and various digital media available across the internet (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2024, p. 8).

3. **Definition of "Prompt Engineering" Technology:** "Prompt" is translated in automated literature as "stimulus," "immediate command," or "guidance." It also takes several designations in the Arab world, such as prompt formulation or structural engineering, elicitation engineering, and inducement engineering. According to the Arabic Python Community, which is one of the pioneering communities in artificial intelligence news within the Arab region, it was translated as "elicitation engineering" for prompt engineering, and "context engineering" for context engineering. However, the common usage is "prompt engineering" , considering it the art of formulating instructions, commands, and inputs for artificial intelligence to obtain the best professional result.

Consequently, the prompt is a modern technical term used to describe the skill of intelligently formulating commands and instructions when dealing with artificial intelligence models, and it poses a translational challenge between terminological accuracy and ease of Arabic circulation. It "is a text or explicit instruction in natural language entered into a Large Language Model (LLM) to guide it to construct a specific response" (Jurafsky, D., & Martin, J. H. (2024), p. 213), as well as (Saudi Data and AI Authority [SDAIA], p. 17).

4. **Formulation and Generation of Cognitive Linguistic Hypotheses:**

A. Formulating Linguistic Hypotheses: In applied and corpus linguistics studies, hypothesis formulation is defined as: "transforming general research questions about language behavior or linguistic phenomena into explicit mathematical or empirical relationships between an independent variable and a dependent variable that is measurable and falsifiable" (Rasinger, S. M. (2018), p. 49-61). Among the sources of hypotheses is that intelligent, scientific guesswork occurring at the brain level within fractions of a second to explain a linguistic phenomenon by finding the relationship between variables through study and analysis based on observed language data to deduce the operating mechanisms of the mind (Bouchlouche Souad, Matali Layla, 2021, p. 341). Example: If we observe that people pronounce the word "apple" faster than the word "democracy," the linguist poses a hypothesis stating: "Because an apple is a concrete object that we touch and see, the brain recalls it faster than abstract words." This guesswork is called a linguistic hypothesis.

In cognitive linguistics, hypothesis formulation is based on the principle that "the structure of language reflects the structure of human cognition" (George Lakoff, 1987, p. 583). According to Lakoff, the formulation of grammatical and semantic hypotheses must begin from a fundamental premise, which is that "the primary function of language is to convey meaning" and that words serve meanings. Consequently, a correct linguistic hypothesis is one that explains formal rules based on the cognitive and contextual data of the speaker (Geeraerts, D., 2006, p. 4, 5, 6).

From the above, we conclude that formulating hypotheses is either:

- Dependent on the empirical statistical aspect and transforming observations into variables.
- Linking variables to cognitive structures and contexts.

B. Generating Linguistic Hypotheses: The machine does not think like humans, but rather searches for statistical and contextual correlations; the prompt is the tool that narrows down the scope of statistical search within the machine's network to produce high-quality outputs. However, how does the linguist guide the machine to produce cognitive linguistic hypotheses?

To generate accurate cognitive linguistic hypotheses, the prompt must include the following elements (Giray, 2024, p. 4, 6):

- **Persona:** Defining the identity of the machine or the input, for example: a cognitive linguist.
- **Task:** Generating a hypothesis that is testable through empirical experimentation.
- **Context & Theory:** Restricting the machine to a specific theory, such as: network models of semantic memory.
- **Constraints/Format:** Preventing the machine from using loose generalizations and specifying the structure of the response.

The three mentioned elements (Persona, Context and Theory, and Task) are known in prompt engineering under the PTCF (Persona, Task, Context, Format) framework or the RTCF framework (Lin, Z., No. 18"8", p. 45-88).

5. **Concept of Large Language Models (LLMs):** The term LLMs is an acronym for the foreign translation "Large Language Models," or Modeling Cognitive Processes. In academic research and computational linguistics, it is translated into Arabic using several synonymous formulations, the most precise and adopted of which are:

- **Large Language Models :** The most common and widely used translation. It is a literal linguistic translation that describes vast textual collections as (Large Corpora) "major/large corpora" (Saudi Data and AI Authority [SDAIA] (2024), p. 9-12). Therefore, characterizing them as "large" directly links them to the volume of linguistic data fed into them.
- **Massive/Huge Language Models :** This relies on the physical, structural, or technical connotation (International Telecommunication Union [ITU], (2026), p. 11), because the word "massive" focuses on network depth (Deep Learning), specifically on the number of parameters (Billions of Parameters) and the immense computing effort required to operate them. Consequently, this designation mostly leans toward everything related to technical engineering description.
- **Major Language Models :** The formulation "Major Language Models" has been used in international technical reports, such as the International Telecommunication Union report. In critical linguistic analysis, however, this designation was adopted based on the formulation of matching adjectives in Arabic grammar; the word "major" here does not signify size and scale alone, but carries a connotation of importance, priority, and comprehensiveness as foundational models from which multiple sub-applications branch out. This is an eloquent trend frequently found in the philosophical literature of artificial intelligence (Jaafar Nayef Ababneh, 2026, p. 28).

The Practical Concept of the Models: Imagine a person who has read every book, article, post, and internet page written in human history, and memorized how words are arranged after one another. This person does not "understand" what is requested of him, but if he hears you say "The sun...", he can predict with a 99% probability that the next word is "bright." This is the Large Language Model (such as ChatGPT or Claude); a very massive computer program trained on immense volumes of human texts until it became genius at predicting words, constructing sentences, and answering them as if it were a human being.

The Specialized Concept: They are Deep Artificial Neural Networks trained on the statistical prediction of linguistic symbols within their context (Next-token prediction). They rely on processing big data to monitor the interrelationships between semantic fields without the presence of a physical sensory reference.

On the level of textual processing, the launch of Large Language Models (LLMs)—starting with the GPT-1 model—constituted a qualitative leap in generative linguistic capabilities. By 2022, the introduction of text-to-image generation tools such as Midjourney and DALL-E 2, alongside advanced chatbots, made these technologies accessible to the general public, exploding profound cognitive and ethical debates regarding intellectual property rights, the future of creative professions, and the regulations for responsible use of artificial intelligence in scientific research and education (Solanki, 2024)

Second: Cognition and the Boundaries of Terminological Operation Between Automated Processing and Artificial Intelligence:

1. **Cognition: Term and Concept:**

A. Definition of Cognition (Concept of Cognition): The terms circulated in Arabic literature for cognition vary between "al-ʿarfanah" , "al-maʿrifiyyah" , and "al-idrākiyyah" , with the concept of the term being mostly closely linked to neuropsychological studies that monitor brain function and various mental processes related to perception. Proponents of this trend unanimously reject the principle of the autonomy of the linguistic system, emphasizing instead the complete absence of any separation between linguistic knowledge and the rest of the structures of general human thought (Al-Azhar Al-Zenad, 2010, p. 11).

Cognition, or what is termed "Cognitive Science," is also defined as a new interdisciplinary field comprising multiple scientific disciplines that collectively focus on studying the human mind and mechanisms of intelligence. The approach presented by linguist George Lakoff is one of the most precise and comprehensive definitions in this context; he views cognitive science as a modern field that integrates what is known about the mind across diverse academic disciplines such as psychology, linguistics, anthropology, and computational linguistics. This science seeks to provide distinct scientific answers to fundamental questions regarding the nature of the mind, how human experience is given meaning, as well as investigating the nature of the conceptual system and its coherence, and the extent to which all human beings share the same conceptual system and thinking mechanisms (George Lakoff, 1999, p. 3-6).

The table below illustrates the most important differences between:

Perception	Knowledge	Cognition
A sensory experience of the world through the five senses, involving the recognition of environmental stimuli, their transmission to the brain, and subsequently the measures taken in response to these stimuli. In this way, it not only creates our experience of the world but plays a crucial role in our interaction with the environment	The understanding, skill, or information relating to a particular subject, acquired from multiple sources, whether through experience or learning, whether held in the mind of a single person or encompassing the general public, theoretical or practical, explicit or implicit (Abdel Rahman Tohme, ibid., p. 10).	The processes and procedures performed by the brain to acquire and process knowledge through thoughts, experiences, and senses (Abdel Rahman Tohme, 2022, p. 10). - The process of inferential operations within the mind, how utterances are produced and interpreted, and how they manifest discursively (Hanane Mosbah, 2022, p. d).

B. Definition of "Modeling Cognitive Processes" (Modelling Cognitive Processes):

We proceed from the general and simple concept of "cognitive processes" as Gilles Fauconnier tells us, defining them as "the way we think" (Gilles Fauconnier, Mark Turner, 2002, p. 6); meaning "everything that goes on inside the mind" when we think, remember, or speak. However, when we want to explain a specific process from the starting point to the final arrival, that scheme or "operational drawing" is the modeling.

Accordingly, "computational modeling of cognitive processes" (Computational Cognitive Modeling) means creating a computer program, an engineering design, or cognitive structures (Cognitive Architectures)—which are software systems that simulate the human mind and mimic the step-by-step way the human brain thinks to process a certain matter. This aims to transform mental activities (such as retrieving words from semantic memory, or constructing metaphors) from mere abstract biological thoughts into software and mathematical structures and computational simulations that the machine can run and simulate to see the extent of their alignment with the human mind. This is executed through the formulation of linguistic hypotheses and large language models.

2. Artificial Intelligence Between Cognitive Concept and Automated Computational Processing:

A. Cognitive Approach to AI: Definitions characterizing artificial intelligence describe it as "an empirical computational theory to explain and model the operating mechanisms of the human mind, rather than just an engineering tool to automate tasks" (Russell, S., & Norvig, P. (2021), p. 5). This perspective stems from the idea that building an intelligent machine necessitates simulating the perceptual, conceptual, and mental processing systems exercised by humans, such as thinking, problem-solving, learning, and producing meaning based on experience. For this reason, it relies on "cognitive sciences" intersecting psychology, philosophy, linguistics, and neuroscience to design machines capable of understanding, reasoning, adapting, and self-learning from data.

Stuart Russell and Peter Norvig, in their book *Artificial Intelligence: A Modern Approach*, provided an explanation foundational to the cognitive approach and its close relationship with artificial intelligence, stating that:

To say that a machine thinks like a human, one must first possess a method for determining how humans think. They clarify that accessing the human mind is achieved through three primary ways directly related to human thinking methods and cognitive modeling (Ibid., p. 5):

- **Introspection:** Attempting to capture and trace one's own thoughts as they occur.
- **Psychological experiments:** Observing the behavior of the human person while performing tasks.
- **Neurological imaging:** Monitoring the brain and neural impulses during operation.

Once a precise and specific theory about the mind is formulated through these three methods, it becomes possible to transform and model it into a computer program, and this is where artificial intelligence converges with cognitive sciences.

Computing and cognitive science experts agree that artificial intelligence transcends unilateral definitional boundaries to focus on two main ideas. The first includes studying the stages of human thought to understand the nature of human intelligence and its neural mechanisms, while the second deals with simulating these processes and representing them operationally through computers and automated systems (Robotics). In this regard, Elaine Rich and Kevin Knight provide an operational definition of artificial intelligence as: "the study of how to make computers do things at which, at the moment, people are better, or to act in a way that would be called intelligent if performed by a human" (Rich, E., & Knight, K. (1991), p. 3).

This view aligns with the cognitive perspective formulated by Mark Fox, an artificial intelligence scientist and director of the Cognitive Engineering Laboratory at the University of Toronto and Carnegie Mellon, who posits that artificial intelligence, in its epistemological depth, represents the scientific theory concerning how the human mind operates and is modeled (Fox, M. S. (1990), p. 8-12). This conceptual overlap demonstrates that the relationship between cognition and generative artificial intelligence is one of structural integration, as contemporary computational models seek to simulate the very same conceptual systems and mental processes studied by cognitive linguistics.

B. Concept of Automated Processing in Computational Linguistics: The term processing in computational linguistics represents the direct automated application onto natural language corpora and texts, with the aim of altering their structure, transforming their contexts, and innovating new cognitive outputs relying on them; to transform their structural contexts and deduce novel cognitive outputs based on an integration between linguistics, computer sciences, and mathematical modeling (Modélisation). Methodologically, this field is based on a procedural duality that separates the description of linguistic knowledge as a priority for the human linguist from the representation and formal expression of knowledge through flexible algorithms managed by the computational linguist. Accordingly, processing acquires a universal dimension that transcends the boundaries of a single tongue toward absorbing and digitizing the structural characteristics of all natural languages.

As for "automation", it procedurally refers to the entirety of digital operations and activities managed completely by the machine, thereby forming the structural counterpart to the mental and manual operations performed by humans. The engine driving this processing is the computer, as a device originally invented to perform complex arithmetic and logical operations, which forces researchers to develop special software algorithms capable of representing and processing information of a linguistic nature (Delafosse, M., "Automatique", 200[e], p. 45). Automated processing in this context is defined as an organized sequence of computational movements serialized in time, executed by an automated program (Programme automatique) that may be fully or partially automated, in order to deconstruct and reconstruct linguistic corpora in accordance with research needs (Bouanani Mostefa et al., 2021, p. 709-712).

Third: An Applied Model of Advanced Prompt Engineering and Its Application to "Lakoff's Conceptual Metaphor Theory":

Below, we present an applied model for formulating a hypothesis on "Conceptual Metaphor," relying on the following pivotal points:

1. Schema for Model Construction and the Formulation and Generation of Linguistic Hypotheses:

- **The Researcher's Goal:** Studying how the human mind understands the concept of "time" through metaphorical mappings (e.g., time is money, or time is motion).
- **The Linguistic Direction (Prompt):** "Act as a cognitive linguist and base your analysis on George Lakoff's theory. Formulate a testable empirical hypothesis regarding how an Arabic speaker processes the metaphor 'time is spatial distance' when using phrases such as (the future is ahead of us / the past is behind us) compared to cultures that view the opposite."
- **The Expected Machine Hypothesis (LLM Hypothesis):** "The model posits that processing temporal expressions based on spatial motion in the Arabic language activates the motor cortex in the brain faster when linking the future to forward motion, and that any cultural shift (such as viewing the past as being ahead) will lead to a delay in reaction time as a result of cognitive conflict.

We illustrate this in the following diagram:

1/ Modeling Cognitive Processes "Operational Flowchart and Diagram"

Based on the definitional and epistemological foundations established in the "boundaries of cognition" step—particularly George Lakoff's thesis regarding the conceptual system and memory—we will now construct an Advanced Constrained Prompt.

The Goal of this Prompt: To drive the Large Language Model (LLM) to function as an "expert system based on linguistic knowledge" that will model the cognitive processes related to the "Conceptual Metaphor Theory" and generate an applied, testable linguistic hypothesis

2/The Phase of the Linguist Guiding the Machine to Generate Linguistic Hypotheses (PTCF)

Persona: Acting as a professor specialized in Cognitive Linguistics and a computational expert in artificial neural networks.

Task and Hypothesis Formulation:

Hypothesis:
The human brain processes the conceptual metaphor [Time is Motion through Space] by mapping spatial parameters from the sensorimotor source domain onto the abstract temporal target domain. In the Arabic linguistic mind, temporal expressions that align with the dominant egocentric spatial framework (the future is ahead / the past is behind) undergo direct, low-latency cognitive routing. This automatic processing pattern activates the motor cortex and the visual-spatial processing networks, as the semantic structures directly mirror the physical experiences of forward bodily movement.

Independent Variable:
The semantic-spatial alignment direction of the temporal metaphorical prompt presented to the subject (e.g., Congruent Alignment: "The future is ahead of us / The past is behind us" versus Incongruent/Conflicted Alignment: "The past is ahead of us / The future is behind us").

Dependent Variable:
The quantitative behavioral and physiological indicators of cognitive load, measured through reaction time (RT) in milliseconds during a sentence-verification task, and ocular fixation durations via eye-tracking technology.

Empirical Prediction:
Exposure to an incongruent or culturally conflicting metaphorical framework will induce semantic-spatial dissonance. This cognitive conflict will disrupt the established neural mapping pathways, yielding a statistically significant increase in both fixation duration and response latency (reaction time), as the cognitive architecture requires additional processing cycles to reconcile the spatial deviation within the automated semantic network

Linguistic and Formal Competence

3 Comparison Between Human Cognition and Automated Processing

The Embodied Perspective (Mitchell & Krakauer, 2023, p. 19)

When modeling cognitive processes to produce hypotheses, the linguist finds himself choosing between two types of competence within intelligent models:

Formal Linguistic Competence: This is the machine's superior capability to perceive and comply with the syntactic, morphological, and structural rules of language in a manner that appears perfect and error-free (Mahowald, K., et al. (2024, p. 113-130)).

Functional Linguistic Competence: This is the capability to use language as a tool for thinking, problem-solving, and understanding unspoken cultural and social contexts, which is the domain that reflects the "real human mind."

The generation of linguistic hypotheses using artificial intelligence primarily relies on exploiting the machine's immense "formal competence" to organize and link concepts at superior speed; however, it remains in need of the "functional competence" inherent in the linguistic intuition of the human researcher to guide these connections and test their cognitive logic

The Obtained Result: The Dilemma of "Embodiment" and the Limits of Mental Simulation:

The epistemological gap between human and machine cognition lies in the perspective of embodied cognition ("Embodied Cognition"). Humans do not learn concepts like "warmth," "heaviness," or "forward motion" as abstract symbols; rather, they perceive them because they possess a physical body that interacts with the world. This vital embodiment is what constructs "Semantic Memory" and grants words their abstract and metaphorical cognitive dimensions.

In contrast, large language models are "disembodied" (Disembodied) systems; they acquire their knowledge of language from texts only (Text-only) without any sensory testing of the physical world. Therefore, when the machine simulates human cognitive processes to generate linguistic hypotheses, it performs a "semiotic simulation" (Semiotic Simulation) based on the interrelationships of words within the corpus, rather than on a true awareness of perceptual meaning. This absence of the sensory body is the primary justification for the emergence of "linguistic hallucination," where the machine can formulate a syntactically coherent and verbally impressive hypothesis, yet it remains completely isolated from the biological or psychological reality of the human brain.

Conclusion (Al-Mutawakkil Ahmed, 2014, p. 88)

Any computational modeling of human language must take into account that meaning is not merely rigid logical relations, but rather a flexible mental representation linked to memory and extended human experience

2. Comparison and Analysis of Machine-Generated Hypotheses Versus Linguist-Generated Hypotheses in the Study of Semantic Memory (An Applied Study):

In this section, we will conduct a practical test of the automated simulation methodology by monitoring a specific cognitive linguistic dilemma: how abstract concepts and concrete concepts are organized and retrieved within semantic memory in Arabic linguistics.

To achieve this comparison, we invoked two hypotheses:

- **The First Hypothesis:** Formulated by classical cognitive linguistic theories based on the "Conceptual Metaphor Theory."
- **The Second Hypothesis:** Generated via a Large Language Model (LLM) using a "Constrained Prompt" that guides the machine to simulate a human semantic network when recalling these concepts.

The following table illustrates the fundamental differences in structure and content between what was produced by human linguistic intuition and what was formulated by the machine based on statistical weights:

Comparison Dimension	Human Linguistic Hypothesis (Human Intuition)	Generated Machine Hypothesis (Artificial Intelligence)
Hypothesis Text	The brain processes abstract concepts by mapping them onto concrete physical structures (time is distance), utilizing bodily and physical experience	The processing of abstract concepts relies on the density of statistical verbal relationships and co-occurrences within the memory network, without the need for sensory mapping
Independent Variable	The degree of embodiment and sensorimotor experience	The degree of frequency and shared textual contexts (Contextual Density).
Dependent Variable	Reaction time and the activation of the motor cortex.	Node recall time (Activation Spreading Speed) in the computational network
Empirical Prediction	Metaphorical expressions congruent with bodily movement (ahead/behind) are processed faster than deviated expressions	Abstract words with dense semantic neighborhoods are retrieved at the same speed as concrete words if their frequency is equal

The comparative analysis of the two hypotheses reveals a deep methodological gap separating human and machine processing mechanisms:

- **First: Embodiment vs. Corpus:** The human hypothesis stems from the realization of linguists (such as George Lakoff) that the human mind links the abstract to the concrete because humans possess a body that experiences space, effort, and location. In contrast, the machine's hypothesis came dependent on the "Statistical Spreading Activation Model," wherein the machine views that an abstract word like (justice) does not require a body to be understood, but is rather recalled based on its close mathematical links to words such as: law, court, right (George Lakoff & Mark Johnson (1999, p. 19-20)).
- **Second: Precision of Formal Structuring and Blindness to Biological Reality:** The automated hypothesis was distinguished by its superior capability to arrange variables and formulate precise computational predictions amenable to direct quantitative measurement, which proves the machine's efficiency as a highly effective tool for accelerating the construction of the hypothetical framework (Dan Jurafsky & James H. Martin (2008, p. 4, 5)). Nevertheless, the machine's empirical prediction suffers from a "biological blindness"; it completely ignores the neuropsychological changes occurring in the human brain (such as blood flow in the frontal lobe when processing abstraction) and focuses solely on the pure mathematical simulation of relationships between symbols.

The comparison places us before two distinct predictions that define the criterion of "intelligence" in both systems:

Human Prediction (Mind Linked to Body and Biology):

- Humans understand abstract words and unconsciously link them to their bodily movements in physical reality.
- It connects linguistic competence to harmony with bodily movement (ahead/behind), making metaphor an inevitable cognitive mechanism that facilitates and accelerates human understanding.
- Measurement scale: Calculating the brain's response time in milliseconds while reading phrases, and measuring the level of activation and blood flow in the motor cortex.
- Result: This correlation proves that cognitive linguistics is an empirical science that integrates with neuroscience.

- **Automated Prediction (Computer Linked to Statistics and Mathematics):**

- The machine transcends the need for a body, understanding words solely through the language of numbers and matrices.
- Operating mechanism: The computer retrieves abstract words at the same speed as concrete words based on probability calculations, bypassing the obstacle of "sensory embodiment." This demonstrates that statistical semantic neighborhood density and equal frequency are sufficient to allow abstract words to be retrieved as quickly as concrete words within the machine.
- Empirical measurement method: The performance of the computational model is measured empirically by calculating the contextual density and the co-occurrence rate of adjacent words within the database fed into the machine, as well as measuring the spreading speed of digital activation between software nodes within the artificial neural network.
- Result: This digital speed represents the computational metric parallel to biological reaction time in humans.

3. An In-Depth Computational Deconstruction of the Chain-of-Thought Technique and Fauconnier's Conceptual Blending Theory:

A. Prompt Inputs:

The Mental Spaces Theory and the Conceptual Blending Theory developed by Gilles Fauconnier and Mark Turner are among the most complex cognitive theories, because they describe the dynamic, real-time processes that occur in the human mind during the generation of innovative new meanings by merging two independent spaces to produce a blended space (Blended Space) containing an emergent structure (Emergent Structure) that does not exist in either of the inputs (Gilles Fauconnier, Mark Turner, 2002, p. 06).

Input Space 1 (Source) -------------> Generic Space <------------- Input Space 2 (Target)

-----------------------------------> Blended Space (Blend) <---------------------------------

(Simulation via Chain-of-Thought)

Generation of the Emergent Structure and the Automated Linguistic Hypothesis

Simulating this process computationally via generative models was nearly impossible until the emergence of the "Chain-of-Thought Prompting" technique. This technique forces the language model not to jump directly to the final answer, but rather to generate a sequence of intermediate symbols (Tokens) that represent the steps of incremental logical reasoning. Deep analysis shows that engineering the prompt according to the Chain-of-Thought strategy computationally reproduces the quaternary structure of the Conceptual Blending Theory:

1. It guides the model to identify the elements of the first input space (Input Space 1), which represents the space of reality or the concrete aspect.
2. It guides it to identify the second input space (Input Space 2), which represents the space of belief or the abstract domain.
3. It extracts the generic space (Generic Space) by searching for structural correspondence between vectors, representing the blended or conceptual space.
4. It performs the process of selective projection (Selective Projection) to produce the blended space.

When the researcher writes the prompt in this deconstructive manner, the model stops superficial guesswork and simulates the cognitive structure of human thought. This produces linguistic hypotheses about how complex metaphors are constructed in human discourses with very high epistemological accuracy that surpasses simple statistical processing.

B. Hypothesis Generation and Prompt Harnessing for Formulating Accurate Cognitive Linguistic Hypotheses:

To transform this theoretical approach into an applied, computational methodological tool, a rigorous Cognitive Prompting Model must be constructed. Harnessing the prompt requires passing through three primary layers designed in accordance with computational and linguistic data:

- **Cognitive Role Layer:** In this layer, the cognitive and epistemological identity of the model is defined (e.g., "You are a cognitive linguistic analyst adopting the empirical school of George Lakoff").
- **Theoretical Constraints Layer :** The model is provided with operational definitions of the cognitive concepts within which it must restrict its analysis (e.g., "Provide examples of the blended space for 'time is money' according to Fauconnier, and strictly isolate the 'Source Domain' based on matter and money from the 'Target Domain' based on the abstract concept of time, relying on Lakoff's thesis that we 'spend, save, and waste time' based on our sensorimotor embodiment of matter").
- **Hypothesis Generation Layer :** This is the final formulation that requests the model to output the result in the form of testable scientific hypotheses (e.g., "Formulate an explanatory hypothesis illustrating why travel words are used to describe love relationships according to the contemporary theory of metaphor by Andrew Ortony (1993, p. 202). Do not give a superficial answer. Use the 'Chain-of-Thought' technique and process the text via the following computational steps:

A. Monitor verbal collocations (Collocations) that bridge the semantics of time and money.
B. Deconstruct the cognitive mapping (Mapping) and clarify the emergent structure.
C. Formulate an explanatory 'cognitive linguistic hypothesis' regarding the speaker's mental model and its falsifiability.
D. Alert the researcher to any potential 'linguistic hallucination' that might deviate from the text").

The statistical analysis of the outputs of this applied model proves that the accuracy rate of the scientifically generated hypotheses rises significantly. Consequently, the machine transforms from a mere consumer and repeater of texts into a "generative research assistant" capable of drawing the linguistic researcher's attention to micro-semantic links within massive corpora (Corpora) that would otherwise take months of human effort to extract.

C. The Deep Epistemological Gap: Statistical Distributional Semantics vs. Perceptual Embodied Semantics:

Despite these astonishing generative capabilities provided by prompt engineering techniques, rigorous scientific thinking from the perspective of cognitive sciences requires us to address the "fundamental epistemological limits" that separate the machine from humans. Here, we return to Lakoff's strict critique of dry computational approaches.

George Lakoff, in his book *Metaphors We Live By* and in his subsequent theses on "The Embodied Mind" or what is known as embodiment, emphasized that meaning can only arise through the sensorimotor experience of a biological body interacting with a physical world (Lakoff & Johnson, 2003, p. 114). Humans understand the meaning of "up," "down," "inside," and "outside" because they possess a body that stands erect, moves in space, and experiences gravity.

- **Human Cognition [Embodied Semantics]:** Conscious Awareness + Biological Existence + Sensorimotor Experience *The Epistemological Gap (Searle's Dilemma)*
- **Machine Intelligence [Distributional Semantics]:** Mathematical Matrices + Statistical Probabilities of Symbol Co-occurrence
- In contrast, Large Language Models (LLMs) completely lack this embodiment. They exist in a world of "distributional semantics," where meaning is defined mathematically as the "probability of symbols co-occurring together" (Brown et al., 2020, p. 14). The machine does not know the heat of fire or the pain of falling; rather, it only knows that the word "fire" statistically co-occurs with words like "burn, heat, energy."
- This epistemological gap leads to what we term in this research **"**Computational Cognitive Hallucination**."** This is the state in which the language model, under the pressure of the prompt, generates linguistic hypotheses that appear stunningly coherent linguistically and rhetorically, yet when deconstructed scientifically, they prove to be "Empty Hypotheses." These empty hypotheses have no foundation in textual reality or human psychology, but are merely the byproduct of a random convergence of mathematical weights within the neural network.
- This critique brings us back to philosopher John Searle's "Chinese Room" experiment: the machine processes symbols based on their formality and statistical rules without being aware of the true meaning underlying these symbols. Accordingly, prompt engineering must remain a tool for the "probabilistic generation of hypotheses," always subject to filtering, criticism, and conscious human empirical validation (Human-in-the-loop). The human cognitive linguist is the only one capable of breathing awareness and embodiment into those mute hypotheses ejected by the machine's matrices (Al-Kiwani, 2025, website).

Fourth: Epistemological Challenges: The Problem of Machine "Linguistic Hallucination" and the Absence of Embodiment (Embodiment):

1. The Epistemology of Disembodiment :

The "Embodied Perspective" (Embodied Cognition) is the fundamental pillar that distinguishes cognitive linguistics from other linguistic schools. This trend posits that human cognition and language do not operate in isolation from the physical and sensory interaction of the body with the surrounding environment. Humans understand the world and construct their linguistic concepts through the five senses, motor activities, and internal emotions (George Lakoff & Mark Johnson (1999, p. 20)).

When projecting this principle onto Large Language Models (LLMs), a major epistemological gap emerges, known as the "dilemma of the absence of embodiment" (Mitchell, M., & Krakauer, D. J., 2023, p. 22). The machine is an entity that lacks a body and biological consciousness; in shaping its outputs, it relies on learning "symbols from text-only data" (Text-only Data) via their interrelationships, mathematical networks, and statistical probabilities, without any direct connection to the real physical world. Accordingly, when the machine simulates mental processes to generate linguistic hypotheses, it reproduces the "shadows of words" and their probabilistic distribution within corpora. This renders its hypotheses a mere formal simulation that lacks the vital cognitive foundation of human perception (Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell (2021, 2022, p. 616).

2. The Phenomenon of "Linguistic Hallucination" and Its Methodological Risks:

The absence of embodiment and the over-reliance on statistical prediction result in a dangerous structural phenomenon in generative artificial intelligence known as "Linguistic Hallucination." It is operationally defined in this research as: "the model's generation of hypotheses, semantic relationships, or even the fabrication of scientific references, which outwardly appear syntactically coherent and formulated in a rigorous academic style, but are completely erroneous from a cognitive and factual standpoint, and lack any linguistic foundation or biological empirical basis."

Linguistic hallucination manifests in scientific research due to several factors:

- **Over-optimization (Satisfying the User's Request):** By their mathematical nature, models seek to satisfy the prompt (direction). If the linguistic researcher requests a hypothesis that links two illogically distant phenomena, the machine may "fabricate" imaginary links and misleading cognitive sequences to fulfill the request.
- **Confusing Correlation with Causation:** The machine may detect a recurring statistical correlation between two words in the corpus, and subsequently build a flawed causal cognitive hypothesis upon it, whereas the correlation in human usage might stem from an incidental rhetorical or metaphorical context.

3. Limits of Methodological Precision Versus Human Linguistic Intuition:

Faced with these challenges, "Human Linguistic Intuition" emerges as an indispensable epistemological safety valve. The human linguist possesses the capacity for self-evaluation and the verification of hypotheses based on internal conscious awareness and lived experience as a native speaker of the language—attributes that the machine completely lacks.

The role of Large Language Models in formulating hypotheses remains confined to the phase of "Exploratory Generation," where the machine excels at uncovering hidden correlations across massive volumes of textual data that the human mind cannot process all at once. However, the process of "methodological filtering," testing the plausibility of hypotheses, and linking them to biological and psychological reality remains exclusive to the mind of the linguistic researcher. This confirms that the machine cannot operate independently in scientific research, but rather remains an extension tool of human intelligence.

Conclusion:

The research paper concluded with a set of results, which we summarize as follows:

- The study proved that Prompt Engineering techniques transcend their superficial programming dimensions to form an advanced methodological tool within computational cognitive linguistics, capable of stimulating statistical weight matrices to extract latent perceptual patterns in languages.
- The comparative method demonstrated that Large Language Models are statistically capable of simulating Fauconnier's "Conceptual Mappings" and "Conceptual Blending" when guided by advanced reasoning techniques such as Chain-of-Thought, allowing them to generate highly complex and deep linguistic hypotheses.
- The study presented a strict epistemological critique based on George Lakoff's theses regarding embodiment (Embodiment), emphasizing the existence of an existential gap between the distributional semantics of the machine and the embodied semantics of humans. This gap explains the emergence of "computational cognitive hallucination" and necessitates the continuous presence of the human researcher as a mandatory final reference to examine and falsify machine-generated knowledge.
- Deep artificial neural networks are trained on the statistical prediction of linguistic symbols within their context, relying on big data processing to monitor interrelationships between semantic fields without the presence of a physical sensory reference.
- Computational modeling of cognitive processes via "prompt" architectural structures demonstrates the machine's capability to simulate the human mind and mimic the way it thinks, enabling the machine to analyze patterns, learn from errors, and self-evolve without explicit programming for every step.
- Large Language Models converge with the cognitive approach in their reliance on connectionism; the machine does not learn language by being taught rigid grammatical rules, but rather through intensive exposure to textual corpora and the construction of artificial neural networks that mimic, in their mathematical architecture, biological neural connections in the human brain.
- Pairing human intuition with the massive analytical capacity of the machine will propel cognitive linguistic research toward unprecedented horizons of accuracy and speed, reaching a point that transcends the obstacle of abstract biological thoughts into software and mathematical structures and computational simulations that the machine can run and simulate to observe the extent of their alignment with the human mind.
- The machine demonstrated the capability to accelerate the construction phase of the hypothetical framework for linguistic research by a high percentage.
- The research concluded that artificial intelligence is an extension tool for the linguistic researcher's mind, rather than a replacement for it.
- The applied model proved that machine-generated hypotheses cannot be adopted as an authentic alternative to linguistic theory and human intuition; instead, they are classified as "probabilistic maps" that reveal to the researcher how words are distributed within major corpora.
- The applied model demonstrated the role of the "stimulus" or "immediate command" (Prompt) in matching natural language through prompt engineering to simulate the language model, guide it, and statistically constrain its behavior.
- For the machine to generate accurate cognitive linguistic hypotheses, the command must integrate based on specific engineering strategies that include PTCF: defining the persona and professional identity of the model "Persona," restricting it to a specific cognitive theory and context (Context), leading up to defining the required task (Task) to produce outputs that are open to testing and falsifiability.
- The linguistic hypothesis stems from the concept of embodiment, where the human mind links the abstract concept to the concrete physical structure based on sensorimotor experience and neurological biological reality.
- As for the machine, it processes abstract concepts (such as justice) as computational nodes retrieved based on contextual density, frequency, and statistical neighborhood within the vector space, completely isolated from any sensory perception.
- The automated hypothesis was distinguished by its high efficiency in narrowing the mathematical probability space and formulating precise, quantifiable computational predictions, making it an advanced tool for accelerating the construction of hypothetical frameworks and generating non-conventional ideas to link semantic fields.
- Nevertheless, this empirical prediction suffers from a "biological blindness"; it completely ignores the neuropsychological changes occurring in the human brain (such as blood flow in the cerebral cortex and frontal lobe) and focuses exclusively on the pure mathematical simulation of relationships between symbols.
- Among the difficulties faced by the machine is the problem of embodiment; the machine learns language from "texts only," whereas humans learn language because they possess a body that sees, touches, and tastes. This absence renders some of the machine's hypotheses regarding "sensory meaning" deficient.
- Methodological hallucination; the machine may fabricate imaginary neural or linguistic links that do not exist in statistical or biological reality to satisfy the request of the prompt or the researcher.
- Studies still require a precise definition of the cognitive gaps that the machine remains incapable of perceiving in cognitive linguistics, such as integrating the concrete with the abstract, rather than relying on an abundance of syntactic structures at the expense of meaning and context.
- The study foresees the necessity of transitioning toward building "Embodied Artificial Intelligence Models" (Embodied AI) linked to integrated sensorimotor and virtual environments to bridge the gap between computational simulation and the human mind, and developing international standardized guidelines for formulating cognitive prompts to serve future linguistic research.

List of Sources and References:

First: References in Arabic:

1. International Telecommunication Union (ITU). (2026). *Better Data for Artificial Intelligence: Enhancing the Reliability of Massive Language Models*. Workshop Session Reports 239, Geneva.
2. Al-Azhar Al-Zenad, *Cognitive Linguistics: An Introduction and Applications*, Casablanca: Arab Cultural Center, 2010.
3. Amira Nasser Al-Qahtani (March, 2025): *Saudi University Female Students' Perception Toward the Use of Generative Artificial Intelligence Applications (ChatGPT) in Higher Education*, Journal of Education, Vol. 1, No. 131, Sohag University, Kingdom of Saudi Arabia.
4. Barkah Meshnan, Iman Ben Kessir: *Generative Artificial Intelligence in Education: A Global Vision of Challenges and Opportunities*, 2025, Journal of Industrial Economy (Khazartech), Vol. 15, No. 1, Batna, Algeria.
5. Jaafar Nayef Ababneh: *Guide to Arabic Computing Terms (Keeping Pace with the Era of Artificial Intelligence and Automated Language Processing)*, Jordan Academy of Arabic, Publications of the Jordan Academy of Arabic, Amman, Jordan, 2026.
6. Hanane Mosbah: *Intentionality and the System of Discourse of the University Professor Between the Logic of Utterance and Gesture (Faculty of Arabic Language, Literature, and Arts, Batna 1 University as a Model)*, PhD Thesis, Batna 1 University, 2022.
7. Abdel Rahman Tohme: *On Culture, Cognition, and Pragmatics: Interdisciplinary Approaches (Alessandro, Falci, et al.)*, Translated by: Abdel Rahman Tohme and Tharwat Morsi, Dar Knooz Al-Ma'refah, Amman (Jordan), 1st ed., 2022.
8. Abdel Mounem Al-Kiwani: *The Wonder of Artificial Intelligence in John Searle's Philosophy of Mind*, Mominoun Without Borders Institution, November 19, 2025, accessed on: 20/02/2026, 20:20, https://www.mominoun.com/articles.
9. Al-Mutawakkil, Ahmed. (2014). *Functional and Cognitive Linguistics: An Approach to the Organization of Linguistic Knowledge*. Dar Al-Aman, Rabat, Morocco. 2014.
10. United Nations Educational, Scientific and Cultural Organization (2024). *Guidance for Generative AI in Education and Research*, UNESCO, printed in France.
11. Saudi Data and AI Authority (SDAIA). (2023). *Generative Artificial Intelligence in Education*, Digital Dawah Repository, Generative Artificial Intelligence Series (2), Riyadh, https://dawa.center/file/7865
12. Saudi Data and AI Authority (SDAIA). (2024). *Arabic Large Language Models: Current Status and Future Opportunities*. Riyadh: Digital Research and Studies Library.
13. Saudi Data and AI Authority (SDAIA), 2024: *Prompt Engineering - Professional User Guide for Applications and Generative Artificial Intelligence - Knowledge Management and Digital Studies*, Riyadh.

Second: Journals:

1. Bouchlouche Souad, Matali Layla: *Formulating Scientific Research Hypotheses in the Field of Economic, Commercial, and Management Sciences*, Journal of Economic Studies, Vol. 21, No. 02, 2021.
2. Bouanani Mostefa, et al.: *Automated Processing for Teaching the Arabic Language Between the Duality of Cognitive Conception and Artificial Intelligence*, Journal of Atras Academy for Linguistic Studies and Research (ATRAS), Vol. 16, No. 1, 2021.

Third: Foreign References:

1. Andrew Ortony (1993), *Metaphor and Thought*, Cambridge University Press, United Kingdom, second edition.
2. Brown, T., Mann, B., & Kaplan, J. (2020). *Language Models are Few-Shot Learners: Transformer Architectures and Distributional Semantics*. Advances in Neural Information Processing Systems, 33, 1-28.
3. Dan Jurafsky & James H. Martin (2008), *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*, 2nd edition.
4. Delafosse, M., "Automatique", In: *Glossaire de linguistique computationnelle*, Paris: Éditions de 2007.
5. Fox, M. S. (1990). *Reflections on the relationship between artificial intelligence and operations research*. AI Magazine, 11(4).
6. Geeraerts, D. (Ed.). (2006). *Cognitive Linguistics: Basic Readings*. Mouton de Gruyter.
7. George Lakoff, *Women, Fire, and Dangerous Things: What Categories Reveal about the Mind*, 1987, University of Chicago Press, 1987.
8. George Lakoff & Mark Johnson (1999), *Philosophy in the Flesh: The Embodied Mind and Its Challenge to Western Thought*, Basic Books.
9. Gilles Fauconnier & Mark Turner, *The Way We Think: Conceptual Blending and the Mind's Hidden Complexities*, New York, Basic Books, 2002.
10. Giray, M. (2024). *Prompt Engineering for Applied Linguistics: Elements, Examples, Techniques, and Strategies*. Applied Linguistics Research Journal, English Language Teaching; Vol. 17, No. 9, Published by Canadian Center of Science and Education.
11. *How to create better persona prompts using your research context*, miro.com.
12. Jurafsky, D., & Martin, J. H. (2024). *Speech and Language Processing* (3rd ed. draft). Stanford University.
13. Lin, Z. (2024). *Prompt Engineering for Applied Linguistics: Elements, Examples, Techniques, and Strategies*. English Language Teaching, 17(8).

14. Mahowald, K., et al. (2024). *Dissociating language and thought in large language models: a cognitive perspective*. Trends in Cognitive Sciences, 28(2).
15. Mitchell & Krakauer, 2023, *The debate over understanding in large language models*, Proceedings of the National Academy of Sciences (PNAS), Vol. 120, No. 13, 2023.
16. Rasinger, S. M. (2018). *Quantitative Methods: Concepts, Frameworks and Issues*. In L. Litosseliti (Ed.), *Research Methods in Linguistics* (2nd ed.), Bloomsbury Academic.
17. Rich, E., & Knight, K. (1991). *Artificial Intelligence* (2nd ed.). McGraw-Hill College.
18. Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
19. Technical Report ITU-T, *TR.Gen AI-Telecom: Potential requirements and methodology for deploying and assessing generative AI models in telecom networks*, International Telecommunication Union, 03/2025.