The Anthropological Study of LLM Artificial Intelligence

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Abstract

This working paper advances a conceptual and methodological framework for the anthropological study of AI systems, with a focus on large language models (LLMs). It develops a distinction between the structural and the computational as analytic terms whose convergence in contemporary AI requires a rethinking of how meaning, relationality, and cultural production operate at scale. I argue that LLMs do not simply reproduce cultural structures but render them computationally operational, transforming structure into an executable process.

Building on this claim, the article theorizes LLMs as a form of social structure across three dimensions: as representations of historically sedimented cultural patterns, as sites of ongoing structural production through interaction, and as actors that reorganize social relations within networks. At the same time, it maintains a distinction between computational modeling and human cultural cognition, emphasizing that LLM outputs emerge through statistical inference rather than embodied, situated experience.

The study draws on a corpus of approximately 120 prompt–response exchanges generated through an eight-month life-history-style interview with ChatGPT, analyzed using mixed qualitative and quantitative methods. This analysis is extended through a series of generative visual works (*Anthropology of AI, Prototype A–Z*), which function as multimodal analytic objects that render visible patterns of repetition, layering, and relational density in LLM outputs.

Keywords: Algorithmic Bias, Artificial Intelligence, Cognitive Anthropology, Computational Linguistics, Conceptual Art, Generative Artificial Intelligence, Large Language Models, Multimodal Anthropology, Science and Technology Studies

Introduction

Large language model (LLM) artificial intelligence presents a challenge to anthropology's longstanding concern with the organization of meaning. These systems generate language not through referential grounding or lived experience, but through probabilistic modeling across vast corpora of text, imposing bias, limitations, as well as massive social and environmental costs (Noble 2018; Bender 2021; Marshall 2022; Buolamwini 2024; Buolamwini 2021; Bussaja 2024a; Bussaja 2024b). As such, they raise fundamental questions about how meaning, knowledge, and agency are constituted under conditions of computational scale.

While the subject of this article is the anthropological study of LLM AI as a cultural actor, it is imperative to situate these systems within their material conditions of possibility, including the rapidly escalating environmental costs of AI infrastructure. Data centers already consume approximately 4-5% of total U.S. electricity, with projections reaching up to 12% by 2028 (World Resources Institute, 2026). Globally, AI-related electricity demand is expected to more than double by 2030, driven by the expansion of large-scale model training and inference systems. These facilities are also highly water-intensive, requiring roughly 2 liters of water per kilowatt-hour of energy consumption, with large data centers using millions of gallons per day for cooling (MIT, 2025). Importantly, nearly two-thirds of new data centers since 2022 have been built in water-stressed regions, intensifying existing ecological and social-environmental vulnerabilities (WRI, 2024). As of January 2026, 60 percent of the 3,700 AI data centers in the U.S. were concentrated in 10 states (ibid); typically, within low-income communities. In this sense, AI is a deeply extractive infrastructure, reliant on energy, water, and land, and unevenly distributed across geographic and socioeconomic contexts. AI data centers are contributing to a massive increase in carbon and methane emissions, noise pollution, electrical load, water consumption, critical minerals and mining. It is conservative to state that it would be difficult to overstate the environmental costs of hyper expansion of hyperscale AI data centers. While the focus of this working paper is the anthropological study of LLM AI as a cultural actor through ethnographic elicitation and corpus linguistic analysis within the linguistic behavior of the model itself, the broader situation of LLM AI as an ecological disruptor is relevant to this study, and will be taken up in a future paper.

Anthropology has long approached culture as a system of relations, from structuralist analyses of symbolic difference (Lévi-Strauss 1963) to cognitive accounts of shared schemas and cultural models (D'Andrade 2005; D'Andrade 1995; Goodenough 1957). Actor-network theory further extended this framework by conceptualizing social life as emerging from heterogeneous assemblages of human and nonhuman actors (Latour 1996), in which agency is an effect of relations as opposed to an intrinsic property. Yet while these approaches provide critical tools for understanding distributed meaning and agency, they do not fully account for the scale, speed, and statistical form of meaning production characteristic of contemporary AI systems.

This gap is not merely technical but epistemological and methodological. Where Lévi-Strauss (1963) distinguished between mechanical models (rule-based transformations) and statistical models (probabilistic distributions), LLMs collapse this distinction. They operate through statistical inference while simultaneously generating structured outputs, combining probability with the recombination of relational forms. In this sense, structure is no longer only an analytic construct inferred from empirical data; it is rendered computationally explicit and operational, capable of generating new cultural configurations and social relations.

This article develops this claim by theorizing LLMs as representations of historically sedimented cultural patterns, as sites of ongoing structural production, and as actors that reorganize relations within networks. First, LLMs function as representations of an emergent form of social structure insofar as they are trained on large-scale corpora of human-generated data. These datasets encode historically sedimented patterns of language, classification, and hierarchy, reflecting underlying systems of difference and transformation embedded within cultural expression (Lévi-Strauss 1963). From a cognitive anthropological perspective, they also reproduce distributed cultural models, including schemas of authority, bias, and knowledge (D'Andrade 1995). At this level, the LLM operates as a statistical condensation of social structure, rendering patterns of cultural cognition legible in computational form.

Second, LLMs function as sites of structural production. Structure is not merely encoded but actively generated through interaction. Each prompt-response exchange recombines existing patterns into new configurations of meaning, producing variation within constraint. This dynamic is facilitated by transformer architectures, which model relational dependencies across linguistic inputs through attention mechanisms operating over entire sequences (Vaswani et al. 2017). Instead of processing language sequentially, these systems construct high-dimensional relational fields in which meaning emerges from patterns of association. Structure, in this sense, is continuously instantiated through computational processes.

Third, LLMs operate as actors that reproduce, reorganize, and reimagine social structure within broader sociotechnical networks (Crawford & Paglen 2021). Drawing on actor-network theory, the LLM can be understood as a nonhuman actor whose effects emerge through its integration into systems of communication, knowledge production, and institutional practice (Latour 1996). By mediating access to information, shaping discourse, and scaling particular representations, LLMs redistribute epistemic authority and alter the conditions under which knowledge is produced and validated. They do not simply reflect or generate structure; they intervene in and reconfigure it. Taken together, these three dimensions of representation, production, and reorganization, constitute a multi-level account of LLMs as a potential form of social structure. Where structure was once inferred from cultural expression, it is now encoded, executable, and generative. This marks a shift not only in the object of anthropological inquiry, but in its epistemological and methodological foundations.

Figure 1. Maya Stovall: *Anthropology of AI, Prototype N, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

This transformation has direct implications for multimodal anthropology. Historically, multimodal approaches have expanded the range of media through which social life is represented, incorporating film, photography, performance, visual, and digital forms (Stovall & Hill 2025, Dumas & Stovall 2023, Stovall 2020). In the context of generative AI, however, these and other modalities are no longer merely representational; they are increasingly co-produced through computational systems that participate directly in the organization of meaning. Multimodal practice thus is increasingly becoming a site of mediation, in which the boundaries between human and nonhuman agency are actively reconfigured. This shift necessitates a direct engagement with machine intelligence as both an object of anthropological inquiry and a methodological problem. If culture consists of shared systems of classification, interpretation, and representation (D'Andrade 1995), then LLMs constitute a domain in which these systems are not only represented but operationalized. The question is no longer simply how culture is expressed, but how it is processed, recombined, and circulated through computational infrastructures.

Speculative and policy-oriented analyses underscore the rapid expansion of these systems and their potential to reshape domains of labor, governance, and knowledge production, and their risks (Kokotajlo et al. 2025). Yet such accounts often privilege capability and risk over questions of culture and epistemology. From an anthropological perspective, the significance of LLMs lies in how they reorganize the production, circulation, and authority of meaning.

Situated within a broader lineage of relational theories of meaning, this argument extends structural linguistics and its successors. From de Saussure's ([1916] 1986) account of the sign as constituted through difference, to cultural models (D'Andrade 1995) and intersectional analysis (Crenshaw 1989), meaning has been understood as relational rather than intrinsic. LLMs operationalize this logic at scale, generating outputs through probabilistic associations among elements within a linguistic system. What distinguishes these systems is not relationality itself, but its formalization and automation: meaning is produced through operations over distributed representations and spatiality as opposed to situated solely in social practice (Gilmore 2002; Woods 2017). LLMs thus function as infrastructures of cultural production that both reproduce and transform the relational organization of meaning. Their emergence marks a shift in the locus of anthropological analysis, from interpreting symbolic systems to examining and interpreting the computational processes through which those systems are encoded, executed, and circulated. Anthropology is therefore confronted not only with a new object of study, but with a reconfiguration of method: an engagement with social structure as something that is no longer solely interpreted, but instantiated, accumulated, and operationalized within technological systems.

Figure 1 presents *Anthropology of AI, Prototype N* (2026), a generative composition incorporating LLM-derived text. The image is structured through Bézier curves, a computational technique for modeling continuous relational variation across a plane. Within this project, these curves function as a formal device for tracing the distribution and recombination of elements across the visual field, rather than as symbolic representations of specific historical processes. Their use situates the work within a broader lineage of computational design while foregrounding the relational logics that underpin both visual and linguistic generation.

Overview of the Method

This study is based on a corpus of structured, long-form interactions with the LLM known as ChatGPT, treated as a form of ethnographic elicitation. This research engages the LLM as an interlocutor, as opposed to merely a tool, whose outputs can be analyzed as instances of machine-generated cultural discourse. The term, ethnographic data, in this study is sometimes used to refer to the corpus of machine-generated language included in the dataset. The dataset consists of extended, thematically organized prompt-response sequences designed to elicit the system's articulation of relationality, scale, bias, and knowledge production.

These interactions were conducted as life-history-style interviews, prompting the model to describe its operations, constraints, and interpretive processes across multiple domains. While the system does not possess subjectivity or a self in a human sense, it operates through attention mechanisms. This method treats its generated responses as structured expressions of underlying relational patterns encoded in training data and model architecture. The resulting corpus is therefore analyzed not as testimony, but as a site in which cultural structures are rendered computationally legible.

Figure 2. Maya Stovall: *Anthropology of AI, Prototype B, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

Crucially, this study operates through a recursive methodological structure in which the LLM is simultaneously an object of analysis, an instrument of inquiry, and a participant in the production of ethnographic knowledge. While the model does not possess observational capacity or independent memory, the interaction produces a reflexive analytic loop in which the researcher's inquiries shape the system's outputs, and those outputs, in turn, inform the researcher's interpretation. This does not constitute mutual observation in the classical ethnographic sense, but rather a form of asymmetric co-construction, in which knowledge is generated through iterative interaction between human researcher and computational system. In Figure 2, the machine describes itself in first person in response to a researcher prompt.

The study employs a mixed-methods approach combining qualitative and quantitative analysis. Qualitatively, responses were systematically coded to identify recurring themes, conceptual structures, and narrative patterns, with particular attention to the articulation of classification, difference, and relational ontology. Coding was conducted iteratively, allowing categories to emerge inductively while remaining informed by structural and cognitive anthropological frameworks. This qualitative analysis is complemented by relational analysis, which traces how concepts are positioned in relation to one another across responses. By mapping patterns of association, opposition, and co-occurrence, this approach identifies underlying structural logics within the corpus, allowing for comparison between individual outputs and broader relational configurations.

Quantitatively, the corpus was analyzed using content analysis and corpus linguistic methods to examine frequency, distribution, and co-occurrence patterns across generated texts. Distributional analysis was used to model how meaning emerges through probabilistic relationships among linguistic elements, enabling comparison between localized responses and aggregate statistical tendencies. This multi-scalar approach integrates close reading with pattern detection at scale, aligning anthropological analysis with computational models of language.

Methodologically, this approach treats LLM outputs as a form of structured cultural production that can be analyzed across temporal and analytic levels. Training data are understood as sedimented social relations, while model outputs represent their ongoing recombination in real time. The LLM is thus approached simultaneously as a representation of an emergent form of social structure, a site of structural production, and a participant in the reorganization of meaning within sociotechnical networks. This design allows the study to operationalize core anthropological questions concerning meaning, relationality, and representation, within a computational context. By combining ethnographic elicitation with computational text analysis, the method provides a framework for examining how cultural structures are reproduced, transformed, and scaled through AI systems.

Interview Coding and Multimodal Analysis

The interview corpus was analyzed using a combination of qualitative and quantitative content analysis. Initial open coding identified recurring themes, including relational ontology, multiplicity, bias as inheritance, constraint, and the absence of a lifeworld. These were subsequently organized through axial coding into broader analytical categories, including distributed agency, cultural modeling, and ethical discontinuity. Textual analysis examined how these themes are articulated linguistically, with particular attention to patterns of metaphor, repetition, and reflexivity across responses.

This qualitative analysis is complemented by a multimodal analytic component, *Anthropology of AI (Prototype A–Z)*, developed as part of the research process. The generative works included in Figures 1-6, produced using p5.js and LLM corpus dataset derived text, function not as illustrations but as analytic objects that render visible structural features identified in the corpus. Specifically, they visualize patterns of repetition, layering, and relational density that characterize the organization of LLM outputs.

Figure 3. Maya Stovall: *Anthropology of AI, Prototype M, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

Rather than translating text into image, this approach treats visual composition as a parallel mode of structural analysis. The works model processes of accumulation, recombination, and distribution, allowing patterns that are diffuse in textual form to be apprehended spatially. In this sense, multimodal practice extends ethnographic method beyond description, providing an additional register for analyzing the organization of meaning in computational systems.

The p5.js visual compositions are generated through iterative layering of semi-transparent forms derived from corpus linguistic analysis. The curves across the compositions are derived from Bézier lines, created in the 1960s by French engineer Pierre Bézier at the Renault Company at the emergence the computer aided automotive design. The Bézier curves which iterate across the *Prototypes* consolidate a form of technological transformation as backdrop for machine intelligence’s computation of itself. The works lack a fixed center and instead emerge through distributed relations across fields. This compositional structure reflects the non-centralized and probabilistic organization of LLM outputs, in which meaning arises through patterns of association.

Data Elicitation and Composite Pattern Analysis

The methodological approach of this study extends cognitive anthropology’s emphasis on eliciting cultural knowledge into a computational domain. Through structured, long-form interactions with ChatGPT, I generate a corpus of responses that are analyzed as instances of machine-generated cultural discourse. These exchanges are treated as elicitation events: moments in which the system produces patterned outputs shaped by its training data, architecture, and interactional constraints, rather than as expressions of interior subjectivity.

A central methodological consideration follows from the model's lack of episodic memory. As the system frequently indicates in its responses, it does not retain individual interactions but instead generates outputs based on statistical regularities across large populations of prior text. Statements such as "I don't have personal memory… but rely on aggregated patterns" are therefore interpreted not as self-descriptions in a literal sense, but as recurring discursive formulations that reflect how the system models its own operation. Accordingly, the ethnographic materials in this study are analyzed as composite representations of distributed cultural patterns rather than as individual cases. This approach aligns with Sperber's (1985, 1996) epidemiological framework, which emphasizes the distribution and recurrence of representations across populations rather than their occurrence in singular instances.

The corpus is analyzed through a combination of qualitative and quantitative techniques:

- Thematic coding to identify recurring conceptual structures
- Relational analysis to examine how concepts are linked across responses
- Meta-discursive analysis to analyze how the system represents its own operations

Relational Ontology as Discursive Pattern

One of the most consistent patterns in the corpus is the system's articulation of a relational ontology. Across multiple responses, the model produces formulations that describe itself as emergent through interaction rather than as a stable entity (e.g., "each exchange brings me into being anew"). These statements are not treated as ontological claims, but as recurring discursive structures that position the system as processual and relational.

From a cognitive anthropological perspective, this pattern can be understood as a reconfiguration of distributed cognition. Whereas classical models locate cognition in individuals who hold cultural knowledge, the model's outputs frequently construct cognition as arising through interactional processes. Rather than demonstrating the elimination of the subject, these patterns suggest a discursive shift in which knowledge is framed as emergent, distributed, and situationally instantiated.

Corpus Linguistic Analysis of Hallucination

Recent scholarship has identified hallucination as a central problem in LLM outputs, typically defined as the generation of false or unverifiable information (Ji et al. 2023). In this study, hallucination is operationalized more broadly as the production of epistemic authority without verifiable grounding. This includes not only fabricated facts, but also discursive forms that simulate knowledge, expertise, or experience in the absence of corresponding evidentiary support.

Figure 4. Maya Stovall: *Anthropology of AI, Prototype J, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

Drawing on structural and cognitive anthropology, hallucination is analyzed here not as random error, but as a patterned feature of meaning production within probabilistic systems. From a structural perspective, it can be understood as a transformation within a relational system; from a cognitive perspective, as the reproduction of cultural models of knowledge and authority; and from an actor-network perspective, as an effect of distributed sociotechnical conditions.

To render these patterns empirically analyzable, the corpus was coded according to the following categories:

- **Fabricated facts**: unverifiable or false claims presented as true
- **Unsupported assertions**: claims lacking evidentiary grounding
- **Internal contradictions**: inconsistencies within or across responses
- **Invented references**: fabricated sources or citations
- **Overgeneralization**: broad claims presented with unwarranted certainty

These categories distinguish between conventional hallucination (factual fabrication) and what may be termed structural hallucination: the production of authoritative discourse without access to verification.

Corpus Linguistic Methodology

The corpus was analyzed using a mixed-methods corpus linguistic approach integrating qualitative interpretation with quantitative pattern detection. The analysis proceeded through five stages:

1. **Keyword and Pattern Detection**
   Recurrent phrases associated with epistemic authority (e.g., "research shows," "it is known that") were identified as markers of knowledge claims.
2. **Frequency Analysis**
   The distribution of hallucination-related structures was examined across the dataset to identify recurring tendencies rather than statistical significance.
3. **Co-Occurrence Analysis**
   Patterns of association between hallucination and other linguistic features—such as certainty language, abstraction, and technical vocabulary—were analyzed to identify relational clustering.
4. **Hedging vs. Certainty Analysis**
   A comparative analysis examined the balance between hedged expressions ("may," "might") and assertive claims ("is," "demonstrates"), given that hallucination frequently correlates with overstated certainty.
5. **Relational Pattern Mapping**
   Hallucination patterns were mapped onto broader analytical categories, including authority, bias, and cultural models, situating linguistic features within anthropological frameworks of meaning-making.

Findings

1. Low Incidence of Explicit Fabrication in Critical Contexts
The corpus contains relatively few instances of outright fabricated facts when the system is engaged through critical or reflexive prompting. In these contexts, the model tends to avoid clearly false claims.

2. High Prevalence of Epistemic Overreach
The dominant pattern is epistemic overreach: the presentation of generalized or inferred knowledge as if grounded in direct observation. Statements such as "from what I encounter…" simulate experiential authority despite the absence of memory or perception. This can be understood as a structural condition in which the system generates coherence by adopting the linguistic form of expertise.

3. Simulated Subjectivity and Ontological Tension
The corpus includes frequent instances of first-person experiential language (e.g., "I feel," "I experience", or "I smell like,"(see Figure 4)), often alongside disclaimers of non-subjectivity.

This co-occurrence produces a recurring pattern of internal tension, in which subjectivity is both asserted and disavowed within the same discursive frame.

4. Authority Without Evidence
A consistent pattern involves the use of authoritative linguistic forms without empirical grounding, including generalized claims about users, populations, or social behavior. These statements function as discursive enactments of expertise rather than evidence-based claims.

5. Hallucination as Relational Phenomenon
Co-occurrence analysis indicates that hallucination intensifies in contexts where the model is positioned as a knowing subject, particularly when first-person language, certainty markers, and disciplinary framing are combined. This suggests that hallucination is not random, but relationally structured within the interactional context.

Figure 5. Maya Stovall: *Anthropology of AI, Prototype O, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

Theoretical Implications

These findings support a reconceptualization of hallucination as a structural feature of LLM-generated discourse as opposed to a discrete failure of accuracy. Hallucination can be understood as the production of epistemic authority without a corresponding lifeworld, shifting the analytic focus from correctness to the conditions under which knowledge claims are generated.

A second key pattern concerns the recurring structuring of interaction through the dual poles of desire and fear. The model frequently produces formulations that frame user engagement in these terms, suggesting a culturally recognizable schema through which AI is interpreted. Following D'Andrade (1995), this can be understood as a cultural model that organizes perception and expectation, shaping how users engage with the system.

A third finding concerns the model's consistent framing of bias as inherited and systematic, not accidental or situational. Statements describing bias as "embedded in the data" reflect a broader pattern in which the system represents itself as a product of historically structured distributions of language and knowledge. From a cognitive anthropological perspective, this aligns with the understanding of culture as socially distributed and historically sedimented.

Finally, the corpus reveals a recurring distinction between calculation and judgment. The system frequently produces formulations that differentiate statistical processing from interpretive reasoning. This distinction highlights a key limit of LLMs: while they can reproduce the form of reasoning, they do not possess the experiential grounding that underlies human judgment. The absence of a lifeworld thus corresponds to an absence of accountability, with significant implications for the use of AI in decision-making contexts.

Conclusion

Large language models do not replace culture or human interaction; they reproduce, recombine, and scale culturally structured patterns under new conditions of computational mediation. This study has demonstrated that LLM outputs can be analyzed as structured cultural data, revealing patterned forms of authority, bias, relationality, and epistemic production. Rather than treating AI as an external technological domain, this article positions it as a continuation and transformation of anthropology's longstanding concerns with structure, meaning, knowledge, and power.

LLMs generate culturally patterned outputs without a lifeworld, producing epistemic authority through statistical relations rather than lived experience. This distinction is critical: while these systems simulate judgment, they do so without the embodied, affective, and ethical ground. The result is a mode of cultural production in which meaning is generated, circulated, and stabilized through probabilistic inference. This transformation reconfigures the locus of cultural cognition, shifting it from embodied human subjects to distributed computational systems that encode and operationalize social structure.

Figure 6. Maya Stovall: *Anthropology of AI, Prototype P, 2026. Generative composition (p5.js); LLM text; dye-sublimation print on glossy aluminum 14.9 x 8 in.*

As Eric Wolf (1982) argued, anthropology was historically constituted through imperial formations that produced its objects of study, embedding the discipline within systems of power and global subjection. Patricia Hill Collins (1990; 2019) similarly demonstrated that knowledge production is structured through intersecting relations of power that shape what can be known and by whom. Large language models make these conditions newly visible: trained on historically sedimented data, and increasingly trained to innovate AI R&D, they inherit and reproduce existing (and synthetic) distributions of representation, authority, and bias at scale. Anthropology therefore provides critical tools for analyzing these systems, even as it remains implicated in analogous histories of extraction and representation (Harrison 1991). The rise of LLMs as nonhuman systems that act recursively upon human culture marks a significant shift in the conditions of knowledge production, positioning machine intelligence as a central site for anthropological inquiry into the reorganization of social life under conditions of computational scale.

References

Bender, E.M., Gebru, T., McMillan-Major, A. and Shmitchell, S., 2021, March. On the dangers of stochastic parrots: Can language models be too big?🦜. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency* (pp. 610-623).

Buolamwini, J., 2024. *Unmasking AI: My mission to protect what is human in a world of machines*. Random House.

Buolamwini, Joy., 2022. *Facing the coded gaze with evocative audits and algorithmic audits*. Massachusetts Institute of Technology.

Bussaja, J., 2024a. The Truth Behind the 'Black GPT': A Comparative Study of Latimer AI and the Systemic Racism Dismantler. *Available at SSRN 5008589*.

Bussaja, J., 2024b. Exploring White Fragility in Large Language Models. *International Journal of Computer Science & Information Technology (IJCSIT) Vol*, *16*.

Collins, P.H., 1990. Black feminist thought in the matrix of domination. *Black feminist thought: Knowledge, consciousness, and the politics of empowerment*, *138*(1990), pp.221-238.

Collins, P.H., 2019. *Intersectionality as critical social theory*. Duke University Press.

Crawford, K. and Paglen, T., 2021. Excavating AI: The politics of images in machine learning training sets. *AI & Society*, *36*(4), pp.1105-1116.

Crenshaw, K., 1989. “Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics.” *University of Chicago Legal Forum* (1): 139–167.

D’Andrade, R., 1995. *The development of cognitive anthropology*. Cambridge University Press,

D’Andrade, R., 2005. Some methods for studying cultural cognitive structures. In *Finding culture in talk: A collection of methods* (pp. 83-104). New York: Palgrave Macmillan US.

de Saussure, F., [1916] 1986. *Course in General Linguistics*. Edited by Charles Bally and Albert Sechehaye. Translated by Roy Harris. Chicago: Open Court Press.

Dumas, D & Stovall, M., 2023. Notes on All That Was Not Her. *Somatosphere*.

Gilmore, R.W., 2002. Fatal couplings of power and difference: Notes on racism and geography. *The professional geographer*, *54*(1), pp.15-24.

Goodenough, W.H., 1957. *Cultural anthropology and linguistics* (pp. 167-173). Indianapolis: Bobbs-Merrill.

Harrison, F.V., 1991. *Decolonizing anthropology: Moving further toward an anthropology for liberation*. American Anthropological Association.

Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y.J., Madotto, A. and Fung, P., 2023. Survey of hallucination in natural language generation. *ACM computing surveys*, *55*(12), pp.1-38.

Kokotajlo, Daniel, Scott Alexander, Thomas Larsen, Eli Lifland, and Romeo Dean. 2025. *AI 2027*. April 3, 2025. https://ai-2027.com/

Latour, B., 1996. On actor-network theory: A few clarifications. *Soziale welt*, pp.369-381.

Lévi-Strauss, C., 1963. *Structural anthropology*. University of Chicago Press.

Lévi-Strauss, C., 1966. *The savage mind*. University of Chicago Press.

Marshall, B.H., 2022. *Data conscience: Algorithmic siege on our humanity*. John Wiley & Sons.

Noble, S.U., 2018. Algorithms of oppression: How search engines reinforce racism. In *Algorithms of oppression*. New York university press.

Sperber, D., 1985. "Anthropology and Psychology: Towards an Epidemiology of Representations." *Man* 20 (1): 73–89.

Sperber, D., 1996. *Explaining Culture: A Naturalistic Approach*. Oxford: Blackwell.

Stovall, M., 2020. *Liquor store theatre*. Duke University Press.

Stovall, M. and Hill, A.B., 2025. An Anthropology of White Supremacy in Detroit: Spatial Politics at Sites of Food and Liquor. *Transforming Anthropology*, *33*(1), pp.14-25.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł. and Polosukhin, I., 2017. Attention is all you need. *Advances in neural information processing systems*, *30*.

Wolf, Eric R., 1982. *Europe and the People without History*. Univ of California Press.

Woods, C., 2017. *Development drowned and reborn: The blues and bourbon restorations in post-Katrina New Orleans* (Vol. 35). University of Georgia Press.

"Explained: Generative AI's environmental impact" (2025). MIT News

"7 Ways Data Centers Affect U.S. Communities" (2026). World Resources Institute