

**The Homogenizing Effect of Large Language Models on Human Expression and  
Thought**

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**Abstract**

Cognitive diversity, reflected in variations of language, perspective, and reasoning, is essential to creativity and collective intelligence. This diversity is rich and grounded in culture, history, and individual experience. Yet as large language models (LLMs) become deeply embedded in people's lives, they risk standardizing language and reasoning. This Review synthesizes evidence across linguistics, cognitive, and computer science to show how LLMs reflect and reinforce dominant styles while marginalizing alternative voices and reasoning strategies. We examine how their design and widespread use contribute to this effect by mirroring patterns in their training data and amplifying convergence as all people increasingly rely on the same models across contexts. Unchecked, this homogenization risks flattening the cognitive landscapes that drive collective intelligence and adaptability.

## The Homogenizing Effect of Large Language Models on Human Expression and Thought

Cognitive diversity, intertwined and manifested through varied linguistic expressions, is essential to the adaptability, creativity, and overall effective functioning of complex societies (Page, 2008). This diversity, shaped by heterogeneous experiences and situated perspectives (Fishman, 1997), plays a critical role in sustaining the epistemic and problem-solving capacities of human groups (Hong and Page, 2004). Variation in expression is not merely stylistic but reflects deeper cognitive and sociocultural differences (Eckert, 2012). When preserved, such distinctions support innovation, prevent epistemic collapse, and enhance the operational efficacy of collective systems (Solomon, 2006; Page, 2008).

This diversity has emerged organically from the coexistence of individuals with distinct backgrounds, linguistic repertoires, and value systems (Labov, 1972; Hofstede, 2001; Evans and Levinson, 2009). Yet, the increasing reach of global communication technologies, while enabling unprecedented knowledge sharing and connection, has also contributed to a gradual contraction of linguistic and cognitive variation (Harmon and Loh, 2010; Cooperrider, 2019; Meakins and Algy, 2016). Among these technologies, Large Language Models (LLMs) have emerged as especially influential, becoming deeply integrated not only within digital infrastructure but also as fundamental components shaping how we interact with technology and with each other (Ver Meer, 2024; Handa et al., 2025). Importantly, their outputs not only mediate traditional language-based tasks such as summarization (Zhang et al., 2024a) and dialogue generation (Yi et al., 2024), but also increasingly serve as proxies for thought (Wu et al., 2024; Binz and Schulz, 2023), identity (Santurkar et al., 2023), and reasoning (Webb et al., 2023), as their generated text increasingly comes to be seen as a reflection of a person's beliefs, personality, or cognitive style.

LLMs are also profoundly reshaping research practices in the cognitive sciences. Their integration into domains such as sociocognitive modeling (Kosinski, 2023),

psychological simulation (Park et al., 2023), even experimentally in place of human participants (Aher et al., 2023; Pellert et al., 2024; Luo et al., 2024; Crockett and Messeri, 2023; Dillon et al., 2023), and ideologically sensitive forecasting (Argyle et al., 2023) expands the scope of what it means for a model to represent human diversity. This integration makes it critical to examine whether these models preserve human diversity or instead enforce a form of cognitive and linguistic homogenization. The risks inherent in this standardization are substantial: homogenized generations may constrain public discourse, reduce the visibility of marginal linguistic forms, and reinforce dominant reasoning templates. They may also suppress the kinds of idiosyncratic language use that signal individual traits or group-specific perspectives (Sourati et al., 2025). In complex reasoning tasks, the widespread adoption of chain-of-thought prompting (Wei et al., 2022b), optimized for linear and explicit inference, may disincentivize abstract, intuitive, or associative reasoning styles that are less easily modeled but critical to pluralistic problem-solving (Sui et al., 2025). These shifts raise broader concerns: that LLMs, if uncritically integrated, may shape not only how we write but how we think.

LLMs thus present a paradox for cognitive science: as they become a powerful tool for modeling human thought (Strachan et al., 2024), they also risk flattening the very cognitive diversity that cognitive science studies (Boogert et al., 2018). With growing concern across linguistics, computer science, psychology, and cognitive science more broadly about the homogenizing effects of LLMs, this review brings these perspectives into conversation. We discuss diversity across three key dimensions: stylistic variation in language, perspective, and cognitive reasoning strategies. By bridging disciplinary boundaries, we aim to provide a more integrated understanding of how generative models interact with human diversity, both reflecting and influencing the diversity present in human expression. Through this cross-disciplinary integration, we surface key issues that future research must engage with and highlight the importance of pluralistic alignment as a principle for developing technologies that serve diverse human populations (Sorensen et al.,

2024).

### Language Models, Prediction, and the Loss of Diversity

Language modeling is central to modern artificial intelligence as it provides the foundation for systems that understand, generate, and interact through natural language. The most powerful language models, large language models (LLMs) such as GPT-4 (Achiam et al., 2023), Claude (Anthropic, 2024), and Gemini (Team et al., 2023), with their advanced and emergent capabilities (Wei et al., 2022a), have transformed fields ranging from education and communication to scientific discovery and policy analysis (Yi et al., 2024; Liu et al., 2023b; Zheng et al., 2025; Cao et al., 2024).

At their core, these models operate by predicting the next token given a preceding context, a goal shared with earlier approaches like  $n$ -gram models that estimated token probabilities using fixed-size word windows and explicit statistical counts from large corpora (Mitchell, 1999). LLMs extend this approach at a much larger scale, trained on massive datasets with billions of parameters, supported by unprecedented levels of compute and architectural optimization (Grattafiori et al., 2024). Despite these advances, their fundamental objective remains the same: mastering the statistical regularities of language through next-token prediction, which remains the dominant driver of model behavior (Lin et al., 2023) even after the application of alignment methods such as instruction fine-tuning (Wei et al., 2021) and preference-based alignment tuning via reinforcement learning from human feedback (RLHF; Bai et al., 2022).

Yet these advances come with structural limitations. Because LLMs are trained to reflect the statistical patterns of their input data, which often overrepresent dominant languages, cultures, and ideologies (Ver Meer, 2024; Handa et al., 2025), their outputs tend to mirror a narrow and skewed slice of human experience. This limitation is not only due to biased training data, but also inherent in the modeling objective itself: next-token prediction favors high-probability continuations, smoothing over outliers, and reinforcing dominant patterns. At scale, what begins as statistical mimicry becomes a generative force

that privileges fluency, coherence, and central tendencies while marginalizing rare expressions, alternative reasoning styles, and culturally specific voices. The consequence is not just a convergence in surface-level linguistic form, but a narrowing of the conceptual space in which models write, speak, and reason. Critically, this narrowing does not trend toward a neutral center but toward a historically uneven one, shaped by the norms, values, and perspectives of English-speaking, Global North, and socioeconomically advantaged populations (Alvero et al., 2024; Hartmann et al., 2023).

This representational imbalance is not static; it becomes an active, homogenizing force through a recursive feedback loop. As individuals increasingly turn to LLMs for writing, problem-solving, and conceptual exploration, the models' outputs, already favoring common linguistic and conceptual patterns, begin to shape the users' own expression, cognitive, and communicative development. In this cycle, the statistical centralizing tendency of next-token prediction is not just reflected in the model's text but is reabsorbed into human discourse, transforming homogenization from a passive bias into a structurally reinforced influence.

This recursive dynamic mirrors the logic of echo chambers (Ross Arguedas et al., 2022), where LLMs' biased and narrow ideologies, universally accessible and widely adopted, often provided by a few dominant commercial platforms, restrict the development of diverse viewpoints. While even small or insular groups can generate internal variation through lived experience and identity, globally shared systems risk preempting that variation before it can emerge. As sociologist George Ritzer argues in his theory of "McDonaldization" (Ritzer, 2021), processes that favor efficiency, predictability, and control often suppress contextual richness. LLMs reflect this logic in the cognitive domain: they offer fluency and consistency but promote a streamlined mode of expression and reasoning that may displace situated, idiosyncratic forms of thought.

In the following subsections, we examine the homogenizing effects of LLMs and how this recursive influence manifests across three interrelated domains: language, perspective,

and reasoning.

### Language Diversity

Human language is deeply rooted in evolutionary and sociocultural diversity. Across time and geography, human groups have developed distinct linguistic systems, cultural norms, and cognitive strategies, shaped by environmental conditions, social structures, and historical contingencies (Fishman, 1997; Eckert, 2012; Hofstede, 2001; Kramsch, 2014). These dynamics are encoded and preserved through language, rich symbolic systems that carry not only information but also values, identities, and culturally situated ways of knowing (Labov, 1972; Bamman et al., 2014; Alvero et al., 2021). Language, in this sense, serves as a powerful medium for expressing cross-language and within-language individual and group differences (Pennebaker, 2011; Boyd et al., 2015), not just through semantic content but also through subtle stylistic, structural, and contextual cues (Walker et al., 2014; Boghrati et al., 2018).

Prior to the rise of LLMs, the exploration of linguistic diversity in NLP unfolded along two parallel but largely separate tracks. The first, focused on generation, aimed to improve the informativeness and simulate natural communication by enhancing surface-level variety. Tasks such as summarization (Dash et al., 2019), translation (Gimpel et al., 2013), ranking (Carbonell and Goldstein, 1998), and dialogue generation (Li et al., 2015, 2016; Vijayakumar et al., 2018; Kulikov et al., 2018; Stasaski and Hearst, 2022) explored techniques to enhance variety and prevent repetition. These included mutual information objectives (Li et al., 2015), diverse decoding strategies such as nucleus sampling (Vijayakumar et al., 2018; Holtzman et al., 2019), and style-conditioned generation (Ficler and Goldberg, 2017). Evaluation metrics (Tevet and Berant, 2020) ranged from lexical distinctiveness (Li et al., 2015) to semantic similarity (Zhang et al., 2019a; Reimers and Gurevych, 2019) and contradiction-based measures (Stasaski and Hearst, 2022). More recent efforts addressed syntactic variation (Huang et al., 2023; Boghrati et al., 2018) and subjective judgments of diversity (Ghandeharioun et al., 2019;

Yang et al., 2019; Zhang et al., 2019b).

Concurrently, a second track of research focused on exploring how language reflects social reality and ways to capture it (Wegmann et al., 2022). Fields like computational sociolinguistics and authorship profiling developed sophisticated methods to identify the linguistic signatures of social position, cultural affiliation, and individual traits like gender, age, and personality (Pennebaker, 2011; El and Kassou, 2014; Neal et al., 2017; Ziabari et al., 2024; Lynn et al., 2017; Nguyen et al., 2021; Cheng et al., 2023). Yet, the primary objective of these works was analytical rather than generative. As a result, a critical disconnect emerged: while one stream of research focused on generating text with surface-level variation, the other illuminated deeper identity- and context-based variation without aiming to reproduce it in generated outputs.

This distinction is particularly important as LLMs are increasingly used to generate text in contexts once reserved for human authorship, which defines a central question: although LLMs have facilitated the improvement of the surface-level variability with prompting in generation, do they also preserve socially meaningful linguistic variation, and do their generations retain interpretable links to speaker traits? Existing evidence suggests they often do not. Sourati et al. (2025) show that LLM-generated texts exhibit reduced stylistic and lexical variability, undermining the ability to infer author characteristics and challenging decades of sociolinguistic assumptions. Alvero et al. (2024) report that LLM-authored college essays disproportionately reflect affluent subgroups and display lower within-group variation. Lee et al. (2025) demonstrate semantic homogenization in LLM outputs compared to human writing. Additional findings by Guo et al. (2023, 2024) indicate that diversity deteriorates when models are trained on synthetic data, and that simple techniques like temperature scaling are insufficient to restore lost variation. Even more concerning, Hayati et al. (2021) show that LLMs attend to different lexical cues than humans when making subjective judgments, suggesting not only a loss of diversity, but a misalignment in what textual cues models prioritize as socially salient. Importantly, Sourati

et al. (2025) also show that this loss is not confined to artificial settings: stylistic variability is decreasing in real-world platforms like Reddit, in scientific writing (Liang et al., 2024), and in peer-reviewed journals, indicating that LLM usage is already reshaping linguistic norms at scale. The problem is exacerbated by the adoption of reinforcement learning, especially RLHF, to improve perceived helpfulness and reasoning capabilities (Bai et al., 2022; Guo et al., 2025). While RL-based techniques have brought clear gains in coherence, instruction following, and reasoning compared to supervised fine-tuned (SFT) models (Chu et al., 2025), they have also been shown to reduce stylistic and expressive variability (Kirk et al., 2023), echoing prior concerns about the quality-diversity trade-off in generative modeling (Caccia et al., 2018; Hashimoto et al., 2019; Zhu et al., 2018; Zhang et al., 2020).

To address these issues, researchers have proposed a range of strategies. Prompting methods aim to counteract default convergence by conditioning generation on more diverse input examples or explicitly modeling response variability to encourage more representative and varied outputs (Wong et al., 2024; Meyerson et al., 2024; Chu et al., 2024; Kambhatla et al., 2025). Beyond prompting, post-training techniques like distribution-matching fine-tuning (Zhang et al., 2024b), reward-based alignment (Xiao et al., 2024; Chung et al., 2025), or other methods focused on designing RLHF pipelines that better retain semantic and lexical diversity without sacrificing quality (Slocum et al., 2025), attempt to recalibrate generation behavior. However, as Lin et al. (2023) show, these adjustments can influence only surface-level token statistics rather than deeper semantic intent. As a result, such interventions remain constrained by the biases and limitations of the pretraining data, which continue to anchor model outputs in dominant writing styles. Moreover, it remains unclear whether such enhanced diversity is grounded in the same sociocultural and experiential foundations as human language variation, rather than being merely superficial.

This representational flattening becomes particularly consequential as these tools move from reflecting linguistic patterns to actively shaping them in daily use. As LLMs become integrated into everyday writing, whether for composing emails, completing

assignments, or exploring ideas, they not only assist but increasingly shape linguistic expression. This influence is not inherently negative: LLMs can make communication more efficient and positively toned, particularly in high-stakes or formal contexts (Hohenstein et al., 2023). Yet such assistance also risks promoting uniform patterns of language that mask the authentic voices of users, including the subtle markers tied to culture, region, emotion, or identity. These effects are not limited to text. Voice assistants, for example, have been shown to alter how people speak, prompting users to soften accents or adopt more socially desirable speech styles (Holliday and Reed, 2025). In both modalities, system expectations act as a pressure toward standardization, subtly shaping language in ways that privilege fluency and niceness over individuality or expressive richness.

This homogenizing effect is increasingly visible in high-stakes domains such as college admissions. LLMs are now used to generate or revise application essays, contributing to a narrowing of what counts as “good” writing (Alvero et al., 2024). Rather than revealing applicants’ unique backgrounds, essays begin to converge on institutionally aligned narratives (Huang, 2024). A similar dynamic has been observed in social media platforms like Reddit, where LLM use is associated with a loss of stylistic variation and linguistic markers that previously revealed individual traits such as personality, demographics, or psychological state (Sourati et al., 2025).

Vitally, these concerns are not confined to the specific domains most recently studied in relation to LLMs. Earlier research on AI-mediated communication, which investigates how technological tools influence tone, content, and user perception, has raised similar alarms across diverse settings, including email writing (Hohenstein and Jung, 2018; Robertson et al., 2021), self-presentation (Jakesch et al., 2019), grammar correction (Dizon and Gayed, 2021), and ideation with memory-augmented systems (Cox et al., 2021). These studies suggest that the homogenization effects observed in more directly studied domains may also be unfolding more broadly wherever AI systems assist communication. Crucially, this influence is not limited to the users themselves: because interpersonal dynamics such

as tone matching and conversational alignment are shaped by language, even those merely interacting with AI-generated text can be affected (Toma, 2014).

### Perspectival Diversity

Individuals vary not only in how they express themselves, but also in the perspectives they hold, the beliefs, values, and interpretive frameworks meaningfully shaped by cultural background, lived experience, ideology, and identity (Plank, 2022). In language, this perspectival variation is reflected in and has been captured in NLP tasks related to sentiment, stance, and framing (Küçük and Can, 2020; Patel et al., 2023; Iliev et al., 2015; Garten et al., 2016).

With the rise of LLMs, this domain of variation becomes especially salient. From interviews and surveys to social media analysis and open-ended writing tasks, a growing number of applications rely on language technologies to interpret (Solangi et al., 2018) or even generate opinions (Salah et al., 2023). As LLMs are deployed in contexts involving ideological reasoning, identity-relevant text generation, and persona emulation (Kim and Lee, 2023), a pressing question arises: do they preserve the pluralism of human perspectives, or do they default to a narrow, socially normative median?

Multiple studies have shown that LLMs tend to reflect dominant, often WEIRD-aligned cultural assumptions in their perspectives (Abdurahman et al., 2024; Atari et al., 2023; Durmus et al., 2023). While models can simulate diverse viewpoints when explicitly prompted, such as by adjusting generation parameters, incorporating identity-coded instructions (Li et al., 2024), or translating prompts to a target language (Wang et al., 2025b; Durmus et al., 2023), these interventions often fall short of aligning outputs with the actual distribution of perspectives within the referenced groups (Santurkar et al., 2023), capture merely the mean of the distribution (Abdurahman et al., 2024), and in some cases, even reproduce out-group stereotypes or misrepresentations of the specified populations (Wang et al., 2025a), highlighting a persistent gap between surface-level diversity and authentic cultural alignment. Hence, while LLMs can replicate

psychological patterns observed in aggregate human data, existing studies indicate that they primarily capture socially “correct” or mainstream opinions (Park et al., 2024), highlighting deeper epistemic and sociolinguistic concerns, namely, that LLMs tend to reinforce essentialized representations of identity (Alvero et al., 2025).

Efforts to explicitly model perspective diversity include multi-agent and multi-persona systems, in which fine-tuned agents are designed to represent contrasting ideological standpoints, including applications such as jury selection, where specialized agents aim to ensure balanced representation of viewpoints (Lahoti et al., 2023; Hu et al., 2024; Gordon et al., 2022). While these approaches can increase semantic spread and lexical variation, their outputs can remain constrained by the framing and content of pretraining data (Lin et al., 2023). Crucially, the extent to which they faithfully reflect the true human distribution of opinions remains an open question. Although LLMs can simulate a broader range of perspectives than any single individual (Lake et al., 2024), their overall variability may still fall short of real-world group diversity (Hayati et al., 2024), and their alignment with population-level distributions is unclear. As Santurkar et al. (2023) argue, structural diversity alone does not equate to genuine human variation, and efforts to diversify outputs must more rigorously test the homogenization hypothesis.

This power to simulate and frame perspectives does not remain contained within the model; it actively shapes users’ viewpoints through repeated interaction. As LLMs become integrated into writing, ideation, and dialogue, they begin to influence how individuals perceive, frame, and evaluate the world, narrowing perspectives rooted in lived experiences central to authentic expression (Hwang et al., 2025). Classic models of ideation and group cognition highlight how environmental cues and shared social settings regulate which memories are activated and which ideas come to mind (Lubart, 2001; Nijstad et al., 2002; Nijstad and Stroebe, 2006; Dougherty et al., 1999). LLMs, however, intervene in this process. By providing the same prompts or completions to millions of users, they introduce a globally shared ideational context.

One setting where this influence is particularly concerning is co-writing with LLM-based assistants that have already been reported to be used in perspective writings (Zhang et al., 2025). Jakesch et al. (2023) demonstrate that participants exposed to LLMs engineered to frame social media posts positively or negatively adopted those framings in their own responses. After co-authoring with the model, participants' survey answers shifted in the direction of the model's bias, showing how LLM-generated language can subtly recalibrate user attitudes. Similarly, Poddar et al. (2023) find that AI-assisted descriptions of personal and professional interests become more polished and institutionally aligned, shaping both self-presentation and self-perception.

This homogenizing influence extends to cultural self-expression. Agarwal et al. (2025) demonstrate that Indian participants using LLMs to write about culturally salient topics (e.g., cuisine) produced essays that became more similar to those of American participants. Analysis based on Hofstede's cultural dimensions (Hofstede, 2001) revealed a loss of region-specific cues such as rituals, collective symbols, and lexical markers, replaced by more generic or Westernized narratives. These shifts raise questions about persuasive influence. As Rashotte (2007) note, social influence can operate independently of coercion or authority, where even mere users' interaction with LLMs may persuade users to adopt the model's language or framing without realizing the shift, especially in the absence of transparency about the model's underlying biases.

Taken together, these findings suggest that LLMs demonstrate "McDonaldization" of perspectival diversity; they lack depth, grounding, variability, and alignment with lived experience that characterize authentic human perspectives. The risk is that LLMs may create the illusion of ideological pluralism while, in effect, collapsing the space of possible viewpoints (Abdurahman et al., 2024), a shift with broad implications for epistemic representation, cultural inclusion, and the interpretive role of language technologies in society. Ultimately, the concern is not just that LLMs alter how people write or speak, but that they subtly reshape what counts as a credible or expressive perspective by repeatedly

making certain framings and mindsets more salient, acting as a form of cognitive priming. As users engage with outputs that underrepresent the true diversity of human experience, they may gradually adopt these framings as normative. In doing so, LLMs not only constrain the spectrum of voices that are heard, recognized, and valued but also reinforce dominant expressive styles, flattening both language and the subjective structures through which people understand and present themselves.

### **Reasoning Diversity**

Beyond language and perspective, another consequential form of diversity at stake is reasoning diversity; the varied ways people reason, solve problems, and generate new ideas. Across disciplines, variation in reasoning is recognized as a key driver of collective strength (Lubart, 2001; Nijstad et al., 2002; Nijstad and Stroebe, 2006; Dougherty et al., 1999). Innovation frequently arises from the recombination of ideas across different domains or worldviews (Muthukrishna and Henrich, 2016), and societal adaptability has been linked to variation in reasoning styles and problem-solving approaches (Henrich, 2004). Intellectual breakthroughs often emerge from engagement with unfamiliar concepts (Duede et al., 2024), and culturally specific reasoning strategies further illustrate this point (Medin et al., 2007). For example, Native American (Menominee) children often grouped animals based on ecological relationships, such as shared habitat or interdependence, whereas European-American children tended to rely on taxonomic categories, which reveals how cultural experience shapes not just what people know, but how they reason about the world (Medin and Atran, 2004).

As LLMs are increasingly deployed in reasoning-intensive settings, from planning and co-writing (Valmeekam et al., 2023; Hwang et al., 2025), to education and collaborative problem solving (Yan et al., 2024; Chen et al., 2024), preserving reasoning diversity becomes crucial. If these systems reflect only a narrow slice of human thought, they risk reinforcing dominant cognitive styles while marginalizing others. Indeed, as Cooperrider (2019) warns, a global “weirdization” may already be underway: once-local

ways of conceptualizing time, space, and causality are giving way to homogenized, Western-aligned models. Trained on massive, biased corpora, LLMs may not only reflect but also amplify this shift (Bender et al., 2021).

This failure to reflect the diverse repertoire of human reasoning manifests in several ways. For instance, Binz and Schulz (2023) demonstrate that LLMs exhibit inconsistent performance across reasoning tasks, sometimes succeeding or failing in ways that diverge from human cognitive patterns. Aher et al. (2023) find that while LLMs perform well on some classic cognitive experiments, they fail to reproduce phenomena such as the wisdom of the crowd, and even more concerning, the boundaries of the alignment and divergence between LLMs and human reasoning are unpredictable (Hagendorff et al., 2022). Perhaps the most accurate description of how LLMs reflect human reasoning is that they approximate an aggregate or statistical center of human judgments (Dillion et al., 2023); however, this comes at the cost of erasing the variation in reasoning strategies, heuristics, and cognitive styles that are foundational to human diversity.

This mismatch may stem from the very objectives used to train and evaluate LLMs, which emphasize measurable performance gains or compliance with verifiable behavioral metrics such as accuracy, informativeness, helpfulness, harmlessness, or formatting consistency (Bai et al., 2022; Glaese et al., 2022; Guo et al., 2025), rather than capturing the richness of human cognitive variation. As a result, most research prioritizes improving reasoning performance over assessing variation in reasoning approaches. Even cognitively inspired methods, such as analogical reasoning in LLMs (Yasunaga et al., 2023), tree-of-thought prompting (Yao et al., 2023), and memory-based inference (Wiratunga et al., 2024), are typically optimized for correctness and general utility. The widespread success of chain-of-thought prompting (Wei et al., 2022b) has further reinforced this narrow focus, encouraging homogenization in both datasets and model outputs (Han et al., 2025; Shao et al., 2024; Liu et al., 2023a). This emphasis on performance, along with over-reliance on techniques that maximize it, carries important consequences: iterative

reasoning models frequently converge on repetitive strategies and struggle to generalize, raising concerns about the adaptability and cognitive diversity of a one-size-fits-all reasoning paradigm (Lingam et al., 2025; Ziabari et al., 2025).

This imperative to maintain diversity extends beyond how LLMs reflect human reasoning to how they influence it. Anderson et al. (2024) find that while users generate more and more elaborated ideas with ChatGPT, the semantic diversity of those ideas is reduced compared to unaided human ideation (Doshi and Hauser, 2024). Users also feel less ownership over the content, attributing creative responsibility more to the model than to themselves, an effect made more concerning by the fact that users rarely attempt to regain control over the generation process. Dang et al. (2023) show that users tend to select from model-suggested continuations based on prior context rather than crafting explicit prompts, effectively deferring to the model whenever its output is “good enough” (Simon, 2019). These tendencies are especially pronounced when LLMs are used early in the ideation process, leading to diminished creativity and lower self-efficacy (Qin et al., 2025).

An emerging but under-discussed concern is the impact of LLMs on the perceived “correct” form and framing of reasoning itself. Prompting paradigms such as chain-of-thought (Wei et al., 2022b), tree-of-thought (Yao et al., 2023), and scratchpad reasoning (Nye et al., 2021) now structure how models generate and explain solutions. As these paradigms are increasingly treated as normative reasoning strategies, they risk becoming internalized by users. If a single model, or family of models, consistently promotes one dominant reasoning structure, this diversity may be eroded. Over time, such convergence could constrain how problems are framed, how alternatives are evaluated, and how knowledge is generated across domains.

These concerns extend beyond the surface structure of reasoning and impact underlying cognitive processes. At the neurocognitive level, Kosmyna et al. (2025) demonstrate that using LLMs during essay writing leads to lower network coherence, reduced semantic integration, and weaker memory retention compared to other information

sources. Users who relied on LLMs showed greater procedural thinking and copying behavior, undermining originality and long-term semantic memory consolidation. In contrast, those who wrote independently before consulting LLMs maintained stronger neural engagement and task ownership, highlighting how tool sequence can materially alter cognitive dynamics.

Taken together, these findings suggest that while LLMs can emulate certain forms of human reasoning, promoting speed, structure, and elaboration, they do not capture the full spectrum of reasoning diversity that makes human thought creative and adaptive. As these systems become more deeply integrated into how people think, learn, and solve problems, they may foster uniformity, stifle ideational diversity, and alter fundamental processes of innovation. If the strength of human cognition lies in its plurality, in the diverse ways people reason, question, and imagine, then preserving this diversity must become a central priority in the design, evaluation, and deployment of LLMs.

## Conclusions

Technological advancements have consistently reshaped human life and society, but LLMs stand out due to the unprecedented scale and unique nature of their influence on human expression and thought. Unlike earlier tools whose impacts were largely confined to specific tasks or domains, LLMs directly affect human language, a medium deeply intertwined with identity, culture, and cognition; human perspectives, shaped by diverse experiences and values; and human reasoning, fundamental to problem-solving and innovation. These three dimensions, language, perspective, and reasoning, are not merely instrumental but encapsulate our collective history, individual experiences, cultural norms, personal identities, and methods of navigating the world. The pervasive integration of LLMs thus carries the significant risk of masking and eroding the intrinsic diversity within these crucial facets of human expression and thought, a diversity that is epistemically and socially meaningful and beneficial.

The unique operational characteristics of LLMs, primarily their training through

next-token prediction on vast, often biased corpora, inherently favor common, dominant patterns. This process leads them to reflect and reinforce standardized ways of expression, perspective-taking, and reasoning, which, coupled with LLMs' prevalence, often limited by a few dominant commercial platforms, result in significant homogenization. Empirical evidence throughout this review has demonstrated the consequences of this phenomenon: from reduced stylistic and lexical diversity in LLM-generated texts (Lee et al., 2025; Sourati et al., 2025), to the subtle recalibration of user attitudes and framing by AI-mediated communication (Jakesch et al., 2023), and the diminished semantic diversity of ideation even as quantity increases (Anderson et al., 2024).

Crucially, these concerns stand to intensify. To meet the substantial data demands of both small-scale and large language models, and given the high cost of human annotation, LLMs are increasingly being used to generate training data for the next generation of models, both in academic research (Long et al., 2024) and large-scale industrial applications (Patel, 2024; Berenstein et al., 2024). Yet if these synthetic augmentations continue to draw from similarly narrow sources or lack stylistic and cultural diversity, they risk reinforcing the very patterns they are meant to diversify. Homogenization becomes cyclical: limited diversity in training produces limited diversity in generation, which in turn shapes user expectations and norms.

This shift, from cognition shaped by personal experience, cultural history, and social context, to cognition increasingly shaped by globally accessible, algorithmically generated content that is shared by millions through a small number of dominant platforms, risks diluting the diversity of individual and collective thought. Such homogenization can have far-reaching societal consequences: LLMs may inadvertently foster more tightly connected global conceptual and reasoning networks, which can lead to a collapse of conceptual variation (Margolin and Monge, 2013). Moreover, while LLMs offer high performance and access to expertise, collective convergence on even optimal algorithms can reduce overall decision-making quality in complex systems (Kleinberg and Raghavan, 2021). Finally, the

use of shared data and models inherently standardizes system outputs, potentially exacerbating structural inequalities by disproportionately shaping individual experiences (Bommasani et al., 2022).

Although proposed solutions to counteract this homogenization, such as pluralistic alignment strategies (Sorensen et al., 2024), embodied reasoning methods (Salali et al., 2024; Vezhnevets et al., 2023), culturally-specific datasets (Aroyo et al., 2023), and diversified prompting, exist (Hu et al., 2024), research in this area remains nascent and insufficiently comprehensive. Currently, the documented negative impacts of LLM-driven homogenization outweigh evidence of successfully fostering diversity. Importantly, future studies must emphasize not just the surface-level distributions of linguistic variation, but also their meaningful connections to the diverse lived experiences and cognitive frameworks that underpin human societies.

In summary, while LLMs offer significant advancements and conveniences, their broad adoption without critical evaluation risks fundamentally altering the diverse cognitive landscapes that enrich human interaction and drive innovation. Moving forward, it is imperative that preserving and enhancing meaningful human diversity becomes a central design and evaluation criterion in LLM development and deployment. Only through deliberate attention to this pluralism can we harness the full potential of language technologies without sacrificing the very diversity that defines human society. Nevertheless, there is still much to learn about the LLM-driven homogenization of language and thought, and how best to address it. Some key directions for deepening this understanding are outlined in the section below.

### Outstanding Questions

- Will current alignment methods, such as instruction fine-tuning and RLHF, ever be sufficient to reproduce the full diversity of human cognition, or are more foundational changes in model architecture, objectives, and training data required? These approaches have increased model steerability and surface-level variation, but it remains unclear whether they can capture deeper context-sensitive and culturally grounded forms of diversity found in human thought.
- Even if LLMs produce more diverse outputs, how can we ensure that this diversity is meaningful and grounded in actual human experience rather than being superficial or artificially constructed? Future research should identify and promote metrics and frameworks that distinguish synthetic variation from diversity reflecting authentic sociocultural, emotional, and cognitive nuance.
- What are the long-term cognitive effects of sustained reliance on LLMs for ideation, writing, and reasoning? While short-term effects such as reduced stylistic variation and creative ownership have been observed, we lack longitudinal studies that track changes in abstraction, memory retention, and reasoning strategies over time and examine whether changes are irreversible.
- Can users be equipped with strategies to counteract the homogenizing effects of LLMs on expression and thought? Research is needed to develop and evaluate behavioral or interface-level interventions, such as delaying LLM use during ideation, or exposing users to model-induced changes, that help preserve agency and individuality in interaction.
- What taxonomies or repertoires of intervention can future research establish to help mitigate LLM-driven homogenization at scale? A systematic understanding of the possible safeguards, behavioral, architectural, or institutional, is needed to guide users, developers, and platforms toward practices that promote cognitive and linguistic pluralism.

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