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# Synthetic English and LLM-mediated writing: A research agenda for register variation and enregisterment

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**Shorter Article**

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**Abstract**

Routine use of large language models (LLMs) is changing how texts are produced and revised, and comparative research has begun to identify recurrent distributional differences between LLM-generated and human-authored English. This article uses the provisional label *synthetic English* (SE) for recurrent linguistic distributions associated with LLM-mediated writing. LLMs operate within existing registers and may redistribute linguistic resources within and across them. Research on stance, textual organization and nominal and informational packaging provides an empirical starting point for this research program, although the direction and strength of these differences vary with genre, task, model and production conditions. The proposed agenda examines linguistic distributions, production processes, circulation, persistence, recognition and social evaluation. Current research provides stronger evidence for recurring production patterns and linguistic distributions than for shared recognition or social meaning. Professionalism, institutional legibility, trust and perceived authenticity are therefore treated as questions for investigation. The article outlines a research agenda using corpus comparison, writing-process evidence, reader judgments and change over time. It closes by considering how rhetorical comparison can help writers examine what LLM-mediated revision changes in their texts and whether those changes suit the writing situation.

## LLM-mediated register variation

Large language models (LLMs) work within and reshape existing registers. Comparative studies increasingly identify measurable differences in the linguistic organization of their output (Mo and Crosthwaite 2025). Indeed, popular descriptions of LLM output have called it a distinctive 'AI style' or 'ChatGPT voice'. Yet this perceived recognizability remains unstable across readers who are asked to identify it. Fleckenstein et al. (2024) found that both novice and experienced teachers were unable to distinguish reliably between ChatGPT-generated essays and student writing, despite expressing considerable confidence in their judgments. Accordingly, recognition must be established through systematic evidence rather than inferred from impressionistic responses. Here, *synthetic English* (SE) provisionally names a research program investigating recurrent linguistic distributions associated with LLM-mediated writing, including differences already documented in comparisons with human-authored English (Reinhart et al. 2025).

Examining LLM-mediated register variation is useful because it integrates questions that are often investigated separately. Biber and Conrad (2019) defined registers as recurrent associations among situations of use, distributions of linguistic features and the communicative functions those features serve. Biber (2012) likewise showed that broad claims about English can conceal systematic situational variation. Agha (2003) provided insights about the process of enregisterment through which repertoires become socially typified and acquire recognizable values as they circulate in use. These traditions direct attention to how LLM mediation redistributes existing linguistic resources across situations of use and how their circulation affects recognition and evaluation.

LLMs draw on linguistic patterns within existing registers and enregistered varieties. As Formosa et al. (2025) found, judgments of authorship change with how much an LLM is used. In practice, then, an academic abstract remains an academic abstract, and a workplace email remains a workplace email even when an LLM contributes substantially to their wording. This is consistent with Bazerman's (1988) account of genres as relatively stable forms that are continually enacted and reenacted through recurrent

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communicative activity rather than fixed properties of individual texts. LLM mediation can thus reshape how a recurring writing practice is expressed without changing its genre or register. The key research question is how repeated LLM use redistributes these linguistic resources as writers draft, revise, seek feedback and reformulate texts.

## A new production configuration

The production configuration of a text is central because LLM-mediated writing is rarely reducible to a simple contrast between a human author and a machine author. Writers may supply an existing passage, request feedback, ask for alternatives, accept or reject suggestions or incorporate only selected parts of a model response. Koltovskaia et al. (2024) showed that graduate students using ChatGPT for academic revision engaged with model suggestions behaviorally through their revision choices, cognitively through noticing and evaluating the feedback, and affectively through their attitudes toward the suggestions. These variations create important distinctions in the composition process because the resulting texts can reflect different distributions of rhetorical work between writer and LLM even when writers report using the same tool. For instance, one writer may retain control over argument and wording while using the model for local revision, and another writer may offload more substantial decisions about phrasing, organization or development to the LLM. I use the term production configuration to refer to these differences in how rhetorical work is distributed during LLM-mediated composition within an existing writing situation or register.

These production configurations occur across a range of registers. Features commonly associated with polished LLM output often draw on linguistic resources that long predate LLMs, including abstract nominal expression and dense informational packaging in academic writing (Biber and Gray 2010). Other recurrent tendencies identified in comparative research, such as explicit organization, patterned stance and recurrent lexical bundles, likewise involve existing resources rather than newly created forms. The empirical question concerns how LLM mediation affects the distribution and recombination of these textual characteristics. Repeated LLM mediation may make some resources more frequent, standardized or portable across settings while reducing their sensitivity to local rhetorical expectations. Evidence from LLM-mediated revision provides a direct illustration of this process. McKinley (2026) found that LLM-mediated polishing reduced hedging and self-mention while shifting academic writing toward more categorical and impersonal forms, which highlights how LLM mediation can alter the distribution of rhetorical resources even when the text begins as human-authored writing.

Model instability within and across LLMs, however, places an important limit on this claim (Muller et al. forthcoming). Comparative research shows that linguistic distributions vary across model families, instruction tuning and writing tasks (Reinhart et al. 2025), while model-version comparisons also identify changes in output over time. LLM responses are also sensitive to prompt formulation, with changes in wording capable of producing different response patterns even when the underlying task remains similar (Chatterjee et al. 2024). These sources of variation make it difficult to attribute a fixed linguistic profile to LLM output. Mak and Walasek (2025), for example, found that several ChatGPT-associated lexical markers increased sharply after 2022 before declining in 2025. They considered several possible explanations for this decline, including changes in the tools or models students used and the deliberate removal of conspicuous AI-associated words. Research into SE should therefore treat candidate features as probabilistic tendencies under specified production conditions.

## Written-register evidence and recurrent choices

To examine this redistribution more closely, the evidence reviewed below identifies three interrelated dimensions that recur across direct comparisons of human- and LLM-generated writing, namely interpersonal regularization, textual-organizational regularization and nominal and informational packaging. Each was selected because multiple comparative studies have found recurrent distributional differences in the linguistic features grouped under that dimension, and because it can be operationalized without first assuming AI authorship. The discussion then turns to studies comparing writing produced before and after the widespread availability of LLMs to examine whether related distributions are appearing in texts produced under real-world conditions of LLM use. Taken together, the three dimensions identify ways in which LLM mediation can redistribute existing resources within and across written registers, with situational variation remaining central to interpretation (Biber and Conrad 2019).

Comparative studies point to systematic differences in how LLM-generated texts distribute organizational, informational and interpersonal resources. Yang et al. (2024) found greater reliance on constant thematic progression and repetitive linking in LLM-generated argumentative texts, while Markey et al. (2024) identified higher informational density and weaker discourse connectivity in ChatGPT output. Reinhart et al. (2025) likewise found systematic grammatical and rhetorical differences between human- and LLM-generated texts, with substantial variation across model types and tasks. Research on argumentative stance shows a related pattern. Liu and Wu (2026) found that ChatGPT-generated texts expressed greater certainty and used fewer concessions before refutation than texts written by English as a foreign language (EFL) learners. Across these studies, the relevant distinction lies in how existing rhetorical and grammatical resources are distributed rather than in the presence of uniquely AI-generated features. The direction and strength of these differences vary across models, tasks, genres and production conditions (Reinhart et al. 2025), which limits any claim that LLM output has a single stable style.

Interpersonal stance and appraisal form one recurrent dimension along which LLM-generated and human-authored writing differ. Mo and Crosthwaite (2025) found that LLM-generated academic writing used a narrower and more

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repetitive repertoire of stance and engagement features, while human writers used significantly more hedges and boosters. Yao and Liu (2025) identified a similar difference in academic book reviews. Although both human and GPT-generated reviews relied heavily on appreciation, or evaluations of things and texts, human reviewers made richer use of affect, which expresses emotion, and judgment, which evaluates people and behavior. They also used engagement resources for positioning toward other voices and graduation resources for adjusting evaluative strength more flexibly than GPT-generated reviews. These findings support interpersonal regularization as a dimension of LLM-mediated register variation while also showing that the direction of particular differences varies across stance and appraisal resources.

Nominal and informational packaging (e.g., noun-based constructions, lexical bundles and patterns of reference) provides another comparatively well-grounded dimension of difference between LLM-generated and human-authored writing. Jiang and Hyland (2025c) compared metadiscursive nouns in 145 ChatGPT essays and 145 student essays. Although their overall frequencies were similar, ChatGPT favored simpler determiner-plus-noun constructions and relied more heavily on anaphoric reference, which points back to information already introduced in the text. Student essays used a more balanced range of syntactic patterns and more cataphoric reference, which anticipates information introduced later. Their earlier study also found greater use of noun- and preposition-based bundles for abstract description in ChatGPT essays (Jiang and Hyland 2025a). These patterns are consistent with broader findings on informational density reported by Markey et al. (2024) and Reinhart et al. (2025). For SE, the relevant tendency concerns recurring differences in how nominal and informational resources are packaged rather than a general claim that LLM-generated writing simply contains more abstract nouns.

Evidence from writing produced before and after the widespread availability of LLMs provides a further perspective on these comparative findings. Kobak et al. (2025) analyzed more than 15 million biomedical abstracts and identified abrupt post-2022 changes in stylistic vocabulary. Their analysis estimated expected 2024 frequencies from trends in 2021 and 2022, providing a pre-LLM baseline against which observed frequencies could be compared. Mak and Walasek (2025) examined 4,820 undergraduate empirical reports written between 2016 and 2025 and likewise identified post-ChatGPT changes that deviated from patterns established across the earlier years of the corpus. Although these studies provide historical baselines, they do not include comparison groups from the same period in which LLM use was absent or unlikely. Even so, the findings provide evidence that distributions associated with LLM-generated writing began changing in naturally occurring texts following the widespread availability of these systems. These historical findings complement the direct human-LLM comparisons discussed above. Table 1 draws on the comparative evidence to identify candidate SE dimensions for investigating LLM-mediated writing with an empirical basis in documented distributional differences.

## Enregisterment, evaluation and LLM-mediated writing

Enregistered varieties contain linguistic resources with established social histories and values (Agha 2003). LLMs draw on these resources, raising questions about how redistribution and circulation affect evaluations of professionalism and effectiveness. Coman and Cardon (2026) found that workplace participants rated AI-generated messages as professional, effective, efficient, confident and direct, although ratings of sincerity and caring were lower in some conditions. Their findings showed that AI-generated language could attract positive evaluations in workplace communication. Further research can examine whether these judgments are associated with particular linguistic configurations, source attribution or features of the communicative situation.

Institutional legibility provides another focus for investigating how LLM-mediated writing is evaluated. LLM-mediated revision may reduce surface errors and make dominant written conventions easier to reproduce, with consequences for multilingual writers. Warschauer et al. (2023) argued that LLMs can give second-language writers greater access to conventionally fluent English, while also creating new inequalities. Effective use depends partly on access to the technology and on the linguistic and digital resources needed to prompt, evaluate and revise its output. They also caution that extensive reliance on AI may complicate the development of writing abilities that learners still need without such assistance. Kuteeva and Andersson (2024) similarly argued that AI can make dominant academic norms more accessible while flattening authorial voice and increasing linguistic homogeneity. These conventions may also be distributed unevenly. Alvero et al. (2024) compared more than 150,000 human college-admissions essays with more than 25,000 GPT-generated essays and found that the LLM texts were stylistically closest to writing associated with higher levels of social privilege. Their findings suggest that LLMs may reproduce linguistic patterns already familiar to more advantaged social groups. Wider circulation of such patterns could increase the institutional value of some forms of written English while making alternative forms of variation less visible and potentially less valued.

Trust and authenticity provide further grounds for examining the social evaluation of LLM-mediated writing. Purcell and colleagues (2025) found that AI-assisted writers produced messages more quickly while eliciting as much trust as writers working without AI. Disclosure of AI assistance also had little effect on recipients' behavioral or stated trust. Raj et al. (2026), by comparison, found that readers evaluated creative writing less favorably when they were told it had been generated by AI, with the penalty partly influenced by lower perceived authenticity. Evaluations of LLM-mediated writing therefore appear to vary with disclosure, genre and communicative situation. Reader-response studies can separate these influences by manipulating linguistic configuration and source attribution independently.

Enregisterment may also involve feedback between evaluation and subsequent language use. Writers who find that explicit staging, evaluative resources or nominal-packaging patterns receive favorable judgments may reproduce those configurations, while conspicuous phrases associated with AI

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**Table 1.** Research-grounded dimensions for investigating synthetic English in LLM-mediated writing

| Candidate SE dimension for investigation | Operational features and illustrative realizations | Evidence from direct human-LLM comparisons | Current evidentiary basis |
|---|---|---|---|
| Interpersonal regularization | Hedges, boosters, attitude markers, self-mentions, engagement markers, appraisal resources such as affect, judgment, appreciation, and graduation, and argumentative resources such as qualifiers, certainty, and concessions | Mo and Crosthwaite (2025) found that LLM-generated academic writing used a narrower and more repetitive range of stance and engagement features than human writing. Jiang and Hyland (2025b) found that student essays used a greater quantity and variety of engagement markers, particularly questions and personal asides. Yao and Liu (2025) found that human-authored academic book reviews used affect and judgment more richly and engagement and graduation resources more flexibly than GPT-generated reviews. Liu and Wu (2026) found greater certainty and fewer concessions before refutation in ChatGPT-generated argumentative texts. | Direct comparative support across several studies, with the particular distributions varying by model, task, and genre. |
| Textual-organizational regularization | Lexical bundles, transition and frame expressions, linking patterns, thematic progression, and explicit organizational cues | Jiang and Hyland (2025a) found that ChatGPT essays contained fewer bundles overall but a higher type/token ratio, with noun- and preposition-based bundles more prevalent and frequently used for abstract description and transitional or structuring purposes. Yang et al. (2024) found greater reliance on constant thematic progression, repetitive additive linking, and repeated concessive signaling in LLM-mediated argumentative texts. | Direct comparative support from studies of academic and argumentative writing, although the particular organizational patterns remain task- and genre-sensitive. |
| Nominal and informational packaging | Noun- and preposition-based bundles, metadiscursive nouns, determiner-plus-noun constructions, nominalizations, anaphoric and cataphoric reference, and informational density | Jiang and Hyland (2025a) found that noun- and preposition-based bundles were more prevalent in ChatGPT essays. Jiang and Hyland (2025c) found similar overall frequencies of metadiscursive nouns but different syntactic and referential distributions, with ChatGPT favoring simpler determiner-plus-noun constructions and anaphoric reference. Markey et al. (2024) found ChatGPT-generated texts to be more informationally dense than authored texts. Reinhart et al. (2025) found that instruction-tuned models overused nominalizations and exhibited a distinct noun-heavy, informationally dense style. | Direct comparative support across several datasets and models, with substantial variation in the particular nominal and informational features involved. |

***Note:*** The summary of evidence quality refers to empirical support for each dimension as a recurrent distributional difference between LLM-generated and human-authored writing.

may be avoided because they attract suspicion. If recurrent LLM-mediated patterns are unevenly distributed across writers, favorable evaluations may also increase the circulation of forms already associated with greater institutional privilege. Further, model developers may alter outputs in response to public criticism and changing user preferences, making some recognizable cues short-lived. Social uptake may consequently reshape the linguistic distributions that readers and institutions may recognize and evaluate. Longitudinal research can trace these interactions among production, recognition, evaluation, disclosure, avoidance and renewed circulation.

## How LLM-mediated patterns can circulate

Repeated LLM-mediated writing provides one route through which a configuration could spread without a central authority. A writer may ask for help with an email, an abstract, a course reflection, a grant summary, a recommendation and a peer review within the same week. Each task has its own register expectations, yet the writer may repeatedly encounter model suggestions that favor similar forms of explicit staging, evaluative phrasing, stance management and nominal packaging. Writers can reject many suggestions and still accept enough local revisions for similar distributions to recur across otherwise different texts.

Persistence beyond the immediate revision encounter offers a second route. McKinley (2026) compared L2 master's writing from 2019 and 2025 and identified a compounding pattern in which the later texts already contained features that LLM polishing subsequently reinforced. The cohort design identified a shift across writing populations while leaving individual persistence open to longitudinal testing. Studies following the same writers across LLM-mediated and unassisted tasks could examine whether structures accepted during earlier interactions later recur without LLM use. Such evidence would help determine the extent to which LLM mediation alters the immediate text and the writer's available repertoire.

Population-level convergence offers a third route. Doshi and Hauser (2024) found that generative AI could improve individual creative outputs at the cost of reducing diversity. Their study highlights creative diversity as a possible concern and offers a potential drawback to repeated and habitual use of LLM systems across texts even when individual writers make locally useful choices. Kobak et al. (2025) analyzed more than 15 million biomedical abstracts to detect population-level linguistic shifts associated with widespread LLM use, illustrating the feasibility of evaluating shifts in linguistic distributions across writing populations.

Institutional incentives can further reinforce these patterns. Writers learn from teachers, editors, reviewers, employers, platforms and AI systems which phrasings are acceptable, efficient, professional or safe. These pressures resemble what Bakhtin (1981) describes as centripetal forces that pull language toward greater centralization and unification. Lillis (2013) applies this idea to writing, where particular resources can become associated with institutionally valued norms. Repeated LLM mediation could add another source of such pressure if similar linguistic resources are repeatedly offered, selected and circulated across writing situations. Recurrent choices can therefore spread without formal institutional prescription. Register analysis provides a way to connect these local selections with population-level distributions and their evaluation across writing situations.

## Research directions

The SE research program coordinates corpus comparison, writing-process research, reader-response research and longitudinal research. Its purpose is to establish which linguistic distributions accompany LLM mediation, how different production configurations introduce them into texts, and whether they persist or circulate across writing situations. The same program examines how readers and institutions recognize and evaluate these resources within existing registers and whether recurrent configurations become socially recognizable or acquire patterned social values through enregisterment. These lines of inquiry can inform one another. Corpus comparisons can identify distributions to trace in process records, while reader responses can identify evaluations to follow over time. Each proposed tendency remains open to qualification or rejection under specified conditions.

Corpus comparison could test the three dimensions in Table 1 across matched writing situations. Human-authored, LLM-generated and LLM-revised texts should be compared within the same genre, task, audience and communicative purpose before researchers examine patterns across registers. Analyses could record model and version, prompt wording, instruction tuning and the extent of human revision, then test whether particular resources recur together and whether apparent regularization survives these controls. For example, an increase in nominal packaging in LLM-revised abstracts could be compared with changes in workplace emails to establish whether the pattern is confined to one register or recurs across situations. Separate analyses of each dimension would allow evidence to support a tendency under specified conditions, narrow its scope or reject it. The program therefore depends on comparing linguistic distributions under documented production conditions.

Process research could connect textual distributions to the allocation of rhetorical work during LLM-mediated writing. Production records could preserve the sequence of revisions and show when particular changes enter a draft. Writing-process research already provides methods for tracing the timing, location, sequence and linguistic character of revisions through keystroke logs, screen recordings and text-change data (Conijn et al. 2022). A study within the SE research program could extend these methods by recording prompts, model responses, accepted and rejected suggestions and subsequent revisions. Researchers could then distinguish human-led augmentation, reciprocal revision and more extensive model-led generation. These records would allow direct tests of whether greater model involvement predicts stronger regularization and whether writers accept changes selectively across staging, stance, evaluation and nominal packaging. Process evidence could also separate distributions

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favored by LLMs from those produced by the ways writers use them.

Reader-response research could examine recognition and evaluation separately. Baseline studies could present unlabeled texts and test whether readers recognize recurring linguistic configurations without asking them to infer authorship from isolated cues. Factorial experiments could then vary linguistic configurations and provenance labels, allowing their separate and interactive effects to be assessed. The same passage, for example, could appear with different combinations of explicit staging, interpersonal regularization and nominal packaging while being identified as human-authored, AI-assisted or AI-generated, or left unattributed. Outcomes could include perceived professionalism, competence, credibility, warmth, authenticity, confidence, readability and disciplinary fit. Such designs would identify whether evaluations are associated with the linguistic configuration, beliefs about AI provenance or interactions between them.

Other possible tendencies belong in the research agenda until comparative evidence justifies adding them to the evidentiary core. Formulaic balance is one candidate. Researchers could operationalize symmetrical constructions, concession-counterclaim sequences, parallel warrants, paired frames and related forms of structural balance, then compare their frequencies across matched human and LLM corpora. Consistent overrepresentation across models, genres and tasks would provide grounds for adding formulaic balance to Table 1. Failure to find such a pattern would remove an intuitively plausible feature from consideration as a proposed LLM-mediated tendency. The same standard should apply to other proposed dimensions. Candidate features gain a place in the framework when comparative evidence shows a recurrent distributional difference.

Longitudinal research could examine persistence and circulation among writers and institutions. The same writers could be followed across periods of AI-assisted and unassisted writing, while classrooms and workplaces could be sampled across successive model versions. Researchers could test whether previously accepted AI revisions recur in later unassisted writing, whether institutional feedback rewards or penalizes particular configurations, and whether writers reproduce or avoid features after those features acquire social salience. These investigations would connect immediate production choices with changes in writers' repertoires and with the circulation and evaluation central to enregisterment.

Together, these studies would assess the proposed tendencies within the synthetic English research program. Evidence could establish which linguistic distributions recur under particular conditions of LLM mediation, trace how those distributions enter writing through different production configurations, and determine whether particular patterns persist or circulate across writing situations. Investigations could also determine whether readers and institutions recognize and evaluate the resulting configurations.

## Pedagogical implications

The SE research program supports a pedagogy of rhetorical comparison. Current evidence is too limited to teach particular words or structures as reliable indicators of AI authorship. A pedagogical use of the research is to examine how LLM-mediated revision redistributes rhetorical resources and how those changes fit particular writing situations. Darvin (2025) argued that critical digital literacy in LLM-mediated L2 writing requires attention to materiality, indexicality and ideology. Wang and Wang (2025) identified critical awareness, critical strategies for human-AI interaction, evaluation of AI affordances and critical positionality among L2 writers. Register awareness gives these broader forms of critical AI literacy a concrete linguistic focus by directing attention to the choices that change when writers work with AI.

Contrastive revision provides one way to develop this awareness. Students can revise the same paragraph in two or more directions and examine how the versions differ in stance, organization, evaluation and informational packaging. Students can then decide which choices serve the genre, audience and rhetorical purposes of their texts.

Register annotation can make these comparisons more precise. Students can mark stance, transitions, evaluative language and nominal packaging in their own drafts and in AI-assisted revisions. Students can then identify the changes and consider their rhetorical effects. A model may improve coherence while reducing authorial presence, simplify a difficult passage while introducing generic evaluation or replace several concrete clauses with an abstract noun phrase.

An AI feedback audit extends this analysis to the advice writers receive. Students could compare model feedback with instructor comments, disciplinary exemplars and their own rhetorical goals. Escalante et al. (2023) found comparable learning outcomes for AI-generated and human feedback among English as a new language learners, while participants identified different advantages in each feedback source. Teng (2024) likewise found that EFL learners generally viewed ChatGPT as a useful source of writing feedback, alongside concerns about its use. An audit could ask students to record which suggestions they accept, reject or rewrite and explain how those decisions affect the resulting text.

Audience comparison broadens register awareness across writing situations. Students can adapt one passage as a journal abstract, workplace email or public explanation, and compare which AI-suggested choices survive. Recurrent staging, evaluative phrasing or nominal packaging across markedly different tasks can indicate where AI assistance is reducing situational variation.

Assessment could support this work by rewarding audience fit, evidence, purposeful stance and justified rhetorical choice alongside the quality of the final text. A short process note could ask students to identify consequential AI-assisted revisions and explain why they retained, rejected or modified them. Such notes provide limited independent evidence of the writing process because they may themselves be generated or substantially revised with AI. Instructors could also examine version histories, annotated drafts or brief in-class explanations of selected revisions.

The pedagogical objective is to preserve rhetorical range. AI assistance can make valued institutional English more accessible, particularly for writers who face disproportionate penalties for surface errors or unfamiliar phrasing. Repeated

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exposure to a narrow set of highly valued forms may also reduce the range of alternatives writers encounter and select. A pedagogy of rhetorical comparison makes these effects available for inspection and gives writers reasons to choose among alternatives according to genre, audience and purpose.

## Conclusion

The synthetic English research program investigates recurrent linguistic distributions associated with LLM mediation, building on documented differences between human-authored and LLM-generated texts (Muñoz–Ortiz et al. 2024; Reinhart et al. 2025). Repeated LLM-mediated production may bring some of these differences into recurring configurations within and across existing registers. Current evidence supports several task-bounded linguistic tendencies associated with LLM-mediated production. Further evidence on whether these tendencies cluster across registers, persist across production settings and attract patterned social evaluation can establish their scope.

The current evidentiary core remains intentionally limited. Interpersonal regularization, textual-organizational regularization and nominal and informational packaging each have direct comparative support. Other plausible tendencies remain candidates for further testing. Reader alignment is also excluded from the evidentiary core because existing findings do not support a consistent directional pattern. Table 1 therefore identifies candidate SE dimensions grounded in comparative evidence and remains open to revision as new studies replicate, qualify or fail to reproduce those differences.

This research program connects forms of evidence that have largely been investigated separately. Corpus research can test whether the candidate dimensions co-occur across models, genres and host registers. Process research can trace how those distributions enter texts through different allocations of rhetorical work between writers and systems. Longitudinal studies can examine whether accepted LLM-mediated forms recur in later writing and whether population-level distributions shift as particular systems become widely used. Reader studies can examine recognition and evaluation separately and test whether judgments follow linguistic configurations, beliefs about AI provenance or interactions between the two. Findings across these lines of research may strengthen, narrow, qualify or reject parts of the SE proposal.

For writers and teachers, SE directs attention toward rhetorical comparison and situated choice. LLM-mediated revision can expand a writer's available repertoire when suggestions are evaluated against genre, audience and purpose. Repeated acceptance of similar defaults across writing situations may also reduce rhetorical range and increase the circulation of forms already treated as institutionally legible or professionally valued. As LLM-mediated writing becomes more ubiquitous, changes in written English can emerge partly through the patterns writers accept, modify and reject, the forms institutions reward and the meanings readers come to associate with their circulation.

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