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THE CATEGORIAL-PRAGMATIC NATURE OF INSTRUCTIONAL DISCOURSE IN COMMUNICATION WITH AN ALGORITHMIC ADDRESSEE

Tulanboev Shokhsuvar
1-year doctoral (PhD) student of
Andijan State Institute of Foreign Languages
+998 93 213 48 68
tulanvoyevshoxsuvor@gmail.com
Doi: https://doi.org/10.5281/zenodo.22292516

Abstract: The rapid spread of large language model interfaces has transformed natural-language instruction from a primarily human-directed discourse practice into a mode of communication addressed to a computational system. This change creates a theoretical problem for linguistics: the discourse retains recognizable directive, procedural, interpersonal, and repair-related properties, yet its addressee cannot be treated as a human interlocutor with embodied experience, socially accountable intentions, or independently established common ground. The present study develops an integrative linguistic account of this emerging configuration. It asks which categorial-pragmatic properties define instructional discourse, how those properties are reorganized when an instruction is directed to an algorithmic addressee, and how grounding and repair shape multi-turn interaction. A purposive corpus of 32 foundational and recent studies in discourse analysis, speech-act theory, procedural communication, human-machine communication, prompt research, conversational grounding, and repair was subjected to deductive-inductive conceptual coding. The synthesis yielded a nine-category model comprising task-intent orientation, directive and deontic force, referential anchoring, contextual and audience specification, procedural sequencing, constraint architecture, output and quality specification, interpersonal calibration, and metadiscursive monitoring and repair. The findings further identify five pressures characteristic of algorithmically addressed instruction: explicitization, modularization, formalizability, asymmetrical grounding, and output-contingent revision. On this basis, a prompt is defined as an instructional macroact whose component microacts regulate not only what is to be done but also the object, conditions, limits, form, and revision of the expected output. The term algorithmic addressee is proposed as a functional discourse role rather than an attribution of consciousness or human-like understanding. The model clarifies the linguistic status of prompts, distinguishes repair from optional refinement, and provides an analytical framework for future corpus-based comparison of instructional discourse across languages.

Keywords: instructional discourse; algorithmic addressee; prompt; directive speech act; pragmatics; conversational grounding; repair; human-LLM interaction

1. INTRODUCTION. Instruction is one of the clearest sites at which language functions as action. An instruction does not merely describe a possible state of affairs; it organizes another participant's conduct by specifying an intended task, a relevant object, a sequence of operations, and a criterion of completion. Classical speech-act theory located commands, requests, advice, and related acts within the directive family because their illocutionary point is to get the hearer to do something (Austin, 1962; Searle, 1969, 1976). Text-linguistic and discourse-oriented studies subsequently showed that instructional communication cannot be reduced to isolated imperative sentences. Procedural discourse typically integrates goals, ordered steps, conditions, warnings, explanations, and

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outcome criteria into a coherent macrostructure (Werlich, 1976; Farkas, 1999; Longacre, 1996). Its linguistic organization is therefore simultaneously grammatical, semantic, pragmatic, and interactional.

Generative language-model interfaces have placed this familiar discourse type in a novel communicative environment. Users now formulate natural-language prompts to request summaries, explanations, classifications, plans, revisions, analyses, and other outputs. Such prompts often look like ordinary human instructions: they employ imperatives, modal constructions, politeness markers, examples, prohibitions, and sequential operators. Yet the interaction cannot be explained simply by transferring the human speaker-hearer model to a computational system. Human interlocutors draw on embodied experience, social roles, shared history, contextual inference, and norms of accountability. A large language model generates text from computationally learned patterns and current input conditions; fluent output alone does not justify attributing human understanding, intention, or consciousness to the system (Bender & Koller, 2020; Shanahan, 2024). A linguistic account must preserve the observable discourse relation without anthropomorphizing its technological participant.

Research in human-machine communication has already challenged the assumption that machines are merely neutral channels. Computational agents increasingly occupy positions that users treat as communicative partners, sources, editors, or assistants (Guzman & Lewis, 2020; Hancock et al., 2020). At the same time, the category of AI-mediated communication is not identical to direct human-AI interaction: in AI-mediated communication, a system may modify messages exchanged between people, whereas prompt-based interaction directly addresses a computationally implemented recipient. The relevant theoretical question is therefore not whether the machine possesses human communicative intention, but how addressivity, response expectation, role assignment, and repair are linguistically organized when the recipient is algorithmic.

Prompt research has largely approached the phenomenon from engineering, human-computer interaction, or model-evaluation perspectives. Prompt catalogs describe reusable structures for controlling model outputs (White et al., 2023), constraint-based studies test compliance with formal or stylistic conditions (Lu et al., 2023), and user studies show that non-specialists often transfer expectations from human instruction to language-model interaction and struggle to articulate requirements systematically (Zamfirescu-Pereira et al., 2023). Requirement-oriented training has consequently emphasized the completeness and precision of the user's specifications rather than reliance on isolated prompting tricks (Ma et al., 2025). These contributions demonstrate that linguistic formulation affects outcomes, but they do not by themselves provide a comprehensive categorial-pragmatic theory of instructional discourse addressed to an algorithmic system.

The interactional dimension makes the problem more complex. Human communication normally depends on grounding, the collaborative process through which participants establish that a contribution has been sufficiently understood for present purposes (Clark & Schaefer, 1989; Clark & Brennan, 1991; Clark, 1996). Recent studies indicate systematic differences between human-human and human-LLM grounding. Shaikh et al. (2025), for example, found that language models in their datasets initiated clarification and follow-up substantially less often than humans, while early grounding failures predicted later breakdowns. Other work shows that model-generated clarification varies according to whether uncertainty is referential or task-based (Madge et al., 2025), and a recent review identifies evaluation of grounding in instruction-following LLMs as an unresolved methodological challenge (Elizabeth et al., 2026). Consequently, prompt-based instruction is not exhausted by the first prompt and first response. It can unfold as a sequence of instruction, output, evaluation, clarification, reformulation, and revised output.

The present study addresses this theoretical gap through an integrative linguistic synthesis. It treats instructional discourse as the broad category, prompt as a technologically situated realization of

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an instructional macroact, and algorithmic addressee as a functional position within discourse. The study is guided by three questions: (1) Which categorial-pragmatic properties are constitutive of instructional discourse in algorithmically addressed communication? (2) How does the algorithmic character of the addressee reorganize the linguistic design of instructions? (3) How should grounding, clarification, repair, and refinement be incorporated into the analytical unit? The objective is not to evaluate a particular model, prescribe a universal prompt formula, or claim that current systems understand language in the human sense. Rather, it is to develop a linguistically explicit model capable of supporting subsequent corpus-based and comparative research.

2. MATERIALS AND METHODS

2.1. Research design. The study employed a theory-building integrative review combined with qualitative conceptual synthesis. This design was selected because the object lies at the intersection of mature linguistic traditions and a rapidly developing body of research on generative AI. A narrowly technical review would underrepresent speech acts, procedurality, discourse structure, politeness, reference, grounding, and repair; a purely classical account would fail to explain the interactional conditions introduced by language-model interfaces. The integrative design therefore combined foundational theoretical works with recent empirical and methodological studies.

The review was purposive rather than exhaustive. Its purpose was to construct an analytically coherent model, not to estimate a pooled effect size. Searches and citation tracing were conducted through August 2026 in the ACL Anthology, ACM Digital Library, Oxford Academic, SAGE Journals, Cambridge Core, and selected open repositories used to locate author manuscripts or bibliographic records. Search combinations included instructional discourse, procedural discourse, directive speech acts, human-machine communication, algorithmic communication, prompt engineering, prompt constraints, conversational grounding, clarification request, referential ambiguity, conversational repair, and LLM politeness. Works were included when they contributed a definition, category, empirical finding, or analytical method directly relevant to the linguistic organization of instructions or to interaction with an algorithmic recipient. Purely technical papers without a communicative or linguistic component, commercial advice pages, and undocumented prompt lists were excluded. The final analytical corpus comprised 32 sources. Eleven established the linguistic foundation of speech acts, discourse, procedurality, common ground, politeness, and repair; eight addressed computer-mediated, AI-mediated, or human-machine communication; and thirteen examined prompting, constraints, user instruction practices, politeness, ambiguity, grounding, or repair in contemporary language-model interaction. The composition of the corpus is summarized in Table 1.

Table 1. Composition and analytical function of the review corpus

Source domain	Number	Primary analytical contribution
Speech acts and pragmatics	5	Directive force, felicity conditions, implicature, politeness, and deontic calibration.
Discourse and procedural text	4	Macrostructure, sequencing, coherence, goal-step relations, and instructional genres.
Grounding and repair	4	Common ground, evidence of understanding, clarification, trouble sources, and repair organization.

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Source domain	Number	Primary analytical contribution
Computer-/AI-mediated communication	6	Technological mediation, machine agency as a communicative position, and social responses to computational systems.
Prompt and LLM interaction research	13	Requirement articulation, constraints, prompt patterns, user difficulties, cross-lingual politeness, model clarification, and grounding failures.
Total	32	Conceptual basis for the proposed categorial-pragmatic model.

2.2. Analytical procedure. Analysis proceeded in three stages. First, deductive codes were derived from established linguistic categories: illocutionary force, modality, reference, context, procedural sequence, politeness, metadiscourse, grounding, and repair. Second, inductive coding was applied to recent prompt and human-LLM studies to identify properties that become especially salient under algorithmic address, including explicit output formatting, constraint stacking, role assignment, requirement completeness, and recurrent user-led reformulation. Third, related codes were consolidated into higher-order categories only when they satisfied three criteria: linguistic observability, functional distinctness, and applicability to both one-turn and multi-turn instruction.

The resulting model was tested against short constructed examples designed solely to demonstrate analytical distinctions. These examples are not presented as natural corpus data and are not used to make frequency claims. They permit controlled comparison between under-specified and elaborated instructions, between repair and refinement, and between human and algorithmic addressee configurations. No inferential statistics were applied because the study synthesizes concepts rather than measuring a participant sample. Reliability was pursued through explicit definitions, negative-case testing, and alignment of each proposed category with multiple strands of the reviewed literature.

A final terminological safeguard guided the interpretation. Algorithmic addressee denotes a functional discourse role occupied by a computational system that receives linguistically formulated input and returns an output treated as responsive. The term does not entail subjective awareness, human intentionality, or human-like semantic understanding. This distinction allows the analysis to describe addressivity and sequential interaction while remaining compatible with critiques of anthropomorphic language about LLMs (Bender & Koller, 2020; Shanahan, 2024).

3. RESULTS

3.1. Instructional discourse as a macroact. The synthesis supports a distinction between an individual directive clause and instructional discourse as a macroact. A clause such as 'Close the file' may realize a directive in a single move. By contrast, an instruction such as 'Review the attached article, identify three methodological weaknesses, preserve the cited evidence, and present the revision in a two-column table' coordinates several microacts: task assignment, object selection, quantitative delimitation, preservation constraint, and output-format specification. The macroact has a single overarching intention - obtaining a specified result - but distributes that intention across functionally differentiated components.

This account explains why grammatical mood alone is insufficient as a defining criterion. Instructions may be realized by imperatives ('List the findings'), modal predicates ('The response must include references'), infinitival or nominal headings ('To verify the result'; 'Output format'), interrogative mitigation ('Could you compare the two models?'), or declarative requirement statements

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('The target audience is first-year students'). Their common property is not a single form but their contribution to the regulation of an expected action or output. Instructional discourse is therefore a functional-semantic configuration whose linguistic forms are selected according to authority, politeness, medium, task complexity, and the presumed capacities of the addressee.

In algorithmically addressed communication, the expected action is commonly a generated text, classification, transformation, plan, or other computationally produced representation. This shifts resultativity to the center of the macroact. The instruction does not merely seek compliance in a general sense; it projects an inspectable output against which requirements can be checked. The output then becomes the basis for a subsequent acceptance, correction, or refinement move. The minimal analytical unit is accordingly not always the isolated prompt but, where interaction continues, the sequence P1 -> R1 -> P2 -> R2: initial prompt, initial response, follow-up instruction, and revised response.

3.2. The nine-category categorial-pragmatic model. Conceptual coding yielded nine recurrent categories. They are analytically distinct but function as an integrated architecture: an instruction can realize several categories in one clause, while a complex prompt can distribute them across headings, sentences, bullet points, or examples. Table 2 presents the model, typical linguistic realizations, discourse functions, and characteristic risks when a category is omitted or under-specified.

Table 2. Categorial-pragmatic architecture of algorithmically addressed instruction

Category	Typical realizations	Primary function	Risk when weak or absent
1. Task-intent orientation	Action verbs; task nouns; purpose clauses; role predicates.	Defines the transformation or action expected from the addressee.	Generic or task-incongruent output.
2. Directive and deontic force	Imperatives; must/should/need to; prohibitions; mitigated interrogatives.	Calibrates obligation, permission, recommendation, and prohibition.	Requirements treated as optional or conflicting.
3. Referential anchoring	Demonstratives; anaphora; file/section labels; quotation; explicit object naming.	Identifies the text, entity, segment, or data to which the instruction applies.	Wrong object, scope, or referent selected.
4. Context and audience specification	Background clauses; genre labels; target-user descriptions; domain terms.	Supplies interpretive conditions, register, and recipient design.	Irrelevant assumptions or unsuitable register.
5. Procedural sequencing	First/then/finally; before/after; numbered steps; conditional branches.	Orders operations and marks dependencies between sub-tasks.	Skipped, reordered, or prematurely executed steps.
6. Constraint architecture	Do not; only; no more than; except; preserve; source restrictions.	Defines boundaries on content, length, evidence, language, and method.	Constraint violation, overgeneration, or omission.

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Category	Typical realizations	Primary function	Risk when weak or absent
7. Output and quality specification	Table/list/paragraph; word limit; tone; criteria such as coherent or evidence-based.	Projects the form and evaluative standard of the expected result.	Correct content in unusable form or quality.
8. Interpersonal calibration	Please; could you; hedges; intensifiers; evaluative stance.	Manages directness, social tone, and perceived cooperation.	Pragmatic mismatch; language-specific performance effects.
9. Metadiscursive monitoring and repair	Check; verify; explain uncertainty; revise; by X I mean; not A, but B.	Regulates interpretation, self-checking, clarification, and correction across turns.	Unnoticed misunderstanding or repeated failure.

Task-intent orientation is the semantic nucleus of the instruction. It answers what operation is required: summarize, compare, classify, translate, diagnose, rewrite, or plan. Prompt studies often treat role assignment as a prompting technique, but linguistically a role statement such as 'Act as an academic editor' is a contextualized predicate that narrows the intended task frame and activates expectations about register, expertise, and procedure. The essential point is not the theatrical role itself but the way it constrains the interpretation of the following directive.

Directive and deontic force determine how requirements are ranked. Imperatives can function as neutral procedural forms rather than expressions of interpersonal dominance, particularly in manuals and digital interfaces. Modal expressions distinguish obligatory components from recommendations or possibilities. In complex prompts, failures can arise when several deontic signals compete, for example when 'be concise' is followed by a demand for exhaustive detail. The relevant unit of analysis is therefore a hierarchy of requirements, not merely the presence of an imperative verb.

Referential anchoring establishes the scope of the action. Minimal forms such as 'improve it' presuppose an accessible referent, but accessibility in a human conversation may depend on gaze, shared activity, or a jointly attended object. In text-based human-LLM interaction, reference is largely reconstructed from the visible conversational record, attachments, interface state, or explicit labels. Expressions such as 'the second paragraph of the attached report' reduce competition among candidate referents. Recent work on clarification confirms that referential ambiguity and task uncertainty trigger different patterns of model behavior (Madge et al., 2025), making the distinction between object identification and task interpretation analytically necessary.

Context and audience specification provide the assumptions that a human addressee might otherwise retrieve from institutional knowledge or the physical situation. Genre, disciplinary domain, communicative purpose, and target readership can change lexical choice, evidential density, syntactic complexity, and explanatory depth. In algorithmically addressed discourse, such contextual information is frequently verbalized because the system cannot be presumed to share a stable social environment with the user. Audience design thus becomes an explicit component of the instruction rather than an entirely tacit pragmatic adjustment.

Procedural sequencing encodes order and dependency. Sequence markers are not decorative cohesion devices: they can determine whether one operation provides input to the next. 'Identify the claims, evaluate the evidence, and then rewrite the conclusion' differs from a list of independent

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requests because the final operation depends on the preceding analysis. Conditional instructions add branching structure: 'If a claim lacks a source, flag it rather than inventing a reference.' Such constructions transform an instruction from a simple directive into a compact decision procedure.

Constraint architecture specifies the boundaries of acceptable execution. Constraint research demonstrates that structural and stylistic requirements provide a productive way to analyze model capabilities and failures (Lu et al., 2023). Linguistically, constraints may be negative, exclusive, quantitative, evidential, temporal, stylistic, or procedural. They can be distributed across several sentences or compressed into modifiers. Requirement-oriented prompting further suggests that output quality depends substantially on the clarity and completeness with which users articulate such conditions (Ma et al., 2025). The category is termed architecture because constraints interact: one can override, narrow, or conflict with another.

Output and quality specification projects the material form of the response and the standard by which it will be accepted. A request for 'a table with columns for claim, evidence, and limitation' differs from a general request to analyze. Quality predicates such as accurate, coherent, accessible, or academically rigorous are less mechanically testable than word limits, but they remain directive components because they establish evaluative expectations. Their vagueness can also create later negotiation: a user may discover only after reading the output what 'concise' or 'formal' should have meant in that task.

Interpersonal calibration concerns how the directive relation is socially framed. Human politeness theories explain mitigation as a strategy for managing face and social distance (Brown & Levinson, 1987), but the same forms can have multiple functions in human-LLM interaction: habit, interface etiquette, emotional self-presentation, or an attempt to influence output. Cross-lingual evidence indicates that impolite wording often degrades performance, while excessive politeness does not consistently improve it and optimal levels vary across languages (Yin et al., 2024). Politeness should therefore be analyzed as a language- and context-sensitive pragmatic variable, not a universal technical command.

Metadiscursive monitoring and repair governs the instruction as an instruction. It includes requests to verify compliance, state uncertainty, ask before assuming, compare the output with criteria, or revise a previous answer. This category connects one-turn prompt design to interactional discourse. It also prevents a false dichotomy between a perfectly engineered initial prompt and system failure: many communicative goals are progressively specified through feedback. The user may not possess a complete requirement representation before seeing the first output; the output itself helps reveal the requirement.

3.3. The algorithmic addressee as a functional discourse role. The second major result is a functional definition of the addressee. In ordinary pragmatics, an addressee is commonly understood as the participant for whom an utterance is designed and from whom uptake is expected. In the present context, uptake is operationally observable through a generated response that is sequentially treated as relevant to the prompt. This is sufficient to establish a discourse role, but not to establish human-like understanding. The algorithmic addressee can therefore be defined as a computationally implemented recipient position to which a user directs natural-language action in expectation of a conditionally responsive output.

This definition separates three levels that are often conflated. At the interface level, the system is addressable: users employ second-person forms, imperatives, vocatives, and role assignments. At the interactional level, outputs form adjacency-like relations with prompts and can be accepted or repaired. At the ontological level, however, the system need not be credited with consciousness, experiential common ground, or moral agency. The distinction is consistent with work in human-machine

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communication that treats technologies as communicative participants while maintaining theoretical caution about the nature of machine agency (Guzman & Lewis, 2020; Esposito, 2022).

Comparison with a human addressee reveals not the absence of discourse but a reconfiguration of its conditions. Table 3 summarizes the contrast.

Table 3. Human and algorithmic addressee configurations

Dimension	Human addressee	Algorithmic addressee
Basis of common ground	Shared environment, history, cultural knowledge, and embodied attention.	Conversation record, supplied context, system configuration, and probabilistically learned patterns.
Status of intention	Socially attributable purposes and commitments.	No human-like intention assumed; responsiveness is treated functionally.
Interpretive resource	Linguistic form plus rich situational and interpersonal inference.	Predominantly textual/multimodal input and available computational context.
Clarification initiative	Reciprocal and normatively expected when understanding is insufficient.	Often asymmetrical and frequently initiated by the user after observing output.
Evidence of uptake	Acknowledgment, action, reformulation, gaze, or subsequent contribution.	Generated response, explicit question, tool action, or output revision.
Accountability	Located in participants and their social roles.	Distributed among user, model behavior, interface design, provider, and deployment context.
Repair ecology	Self- and other-repair embedded in collaborative interaction.	Output-contingent correction, prompt reformulation, context restatement, or restart.

3.4. Five pressures of algorithmically addressed instruction. Across the coded literature, five pressures explain why instructional discourse becomes structurally distinctive when addressed to a language model. The first is explicitization. Information that human participants might infer from institutional routine, physical co-presence, or shared biography is more often verbalized: the relevant document, audience, length, evidence policy, and output format. Explicitization does not mean that longer prompts are necessarily better. It means that pragmatically necessary assumptions are selectively converted into linguistic form.

The second pressure is modularization. Complex prompts frequently separate task, context, constraints, examples, and output format into labeled blocks or bullet points. This resembles procedural documentation and prompt-pattern approaches (White et al., 2023), but its linguistic significance lies in making relations between microacts visually and syntactically inspectable. Modularization reduces attachment ambiguity and facilitates later repair because the user can identify which requirement must be changed.

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The third pressure is formalizability. Users tend to convert qualitative intentions into countable or checkable conditions: number of paragraphs, columns, examples, sources, or words. Such formalization supports compliance assessment, although not all communicative values can be reduced to metrics. Academic rigor, relevance, nuance, and cultural appropriateness remain scalar and context dependent. Effective instruction therefore combines formal constraints with interpretive quality criteria rather than replacing the latter.

The fourth pressure is asymmetrical grounding. Human interlocutors routinely display and test understanding, but contemporary LLM interactions can progress on the appearance of understanding until an output reveals a mismatch. Empirical research reports substantially lower model initiation of clarification and follow-up in some datasets (Shaikh et al., 2025), while theoretical analysis argues that human users often carry the burden of repairing conversational trouble (Pütz & Esposito, 2024). The asymmetry is not absolute - systems can ask questions - but it changes who typically detects and resolves uncertainty.

The fifth pressure is output-contingent revision. In many tasks, users discover the inadequacy of an initial specification only after seeing what it licenses. The first response acts as a diagnostic representation of the prompt. This creates a productive loop in which the user narrows a referent, adds a constraint, changes a format, or recalibrates the audience. The instruction is therefore distributed across turns, and later prompts cannot be analyzed as independent commands detached from the trouble exposed by the preceding response.

3.5. Grounding, repair, and refinement in the interactional cycle. The synthesis supports a four-position interactional model: P1 (initial instructional macroact), R1 (first responsive output), P2 (grounding or revision move), and R2 (revised output). P2 can perform two fundamentally different functions. Repair addresses a recognizable mismatch between the prior instruction and response: the wrong section was summarized, a source was invented, a length limit was exceeded, or a referent was misidentified. Refinement, by contrast, adds or changes a preference that was not violated because it was not previously specified: the user may request a table after receiving an acceptable paragraph or ask for a more concise version without treating the first response as erroneous.

This distinction is important for linguistic analysis. Treating every follow-up as repair would incorrectly classify evolving goals as misunderstandings; treating every follow-up as ordinary elaboration would conceal failures of reference, task interpretation, or constraint compliance. Repair can be initiated by explicit negation ('Not the whole report, only the conclusion'), metalinguistic specification ('By sources, I mean the references already cited'), replacement ('Use X instead of Y'), or restart ('Ignore the previous answer and begin again'). Refinement commonly uses addition, scaling, reformatting, or audience recalibration ('Add one example to each category'; 'Make the explanation suitable for school students').

The following constructed exchange illustrates the analytical difference. P1: 'Summarize the attached paper in no more than 150 words and preserve the citations.' If R1 contains 220 words and alters publication years, P2 - 'Reduce the text to 150 words and keep every author name and year exactly as given' - constitutes repair because explicit constraints were violated. If R1 satisfies the original request and P2 says, 'Now present the same summary as five bullet points,' the move constitutes refinement. In both cases P2 is instructional, but its relation to R1 differs.

Grounding is achieved provisionally when the output supplies sufficient evidence that the relevant task, referent, and constraints have been taken up for the current purpose. This criterion is functional rather than mentalistic. It does not claim direct access to an internal state of understanding. It evaluates the sequential evidence available to the user, consistent with interactional approaches to

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common ground. Because fluent responses can mask misalignment, grounding should be assessed across multiple dimensions: task, referent, content, procedure, format, register, and constraints.

Table 4. Interactional functions of follow-up instruction

Follow-up type	Interactional function	Constructed example
Clarification	Resolves an unclear term, scope, or referent.	By "the results," I mean Table 2 only.
Correction/repair	Replaces an interpretation or output that conflicts with P1.	Do not rewrite the introduction; revise only the conclusion.
Constraint reinforcement	Restates or strengthens an unmet boundary.	Keep the answer under 150 words, including headings.
Procedural repair	Restores a skipped or wrongly ordered operation.	First identify the claims; evaluate them only after listing them.
Refinement	Introduces a new preference without construing R1 as defective.	Now convert the accepted explanation into a three-column table.
Restart	Abandons the current trajectory and establishes a new frame.	Ignore the previous response and begin from the attached text.

3.6. Integrated definition and model. The results permit an integrated definition: instructional discourse in communication with an algorithmic addressee is a goal-oriented, result-projecting, and potentially multi-turn discourse configuration in which a user linguistically regulates a computational system's expected output through task assignment, deontic calibration, referential and contextual specification, procedural ordering, constraints, output criteria, interpersonal stance, and metadiscursive monitoring.

Within this configuration, a prompt is an instructional macroact rather than a mere string or technical command. Its microacts may be explicit or implicit, linearly integrated or modularly displayed, and completed or revised over subsequent turns. The algorithmic addressee is the functional recipient position that makes the prompt answerable, while the generated output is both a response and evidence for evaluating whether sufficient grounding has been achieved. This model links sentence-level form to discourse-level action and links initial prompt design to interactional repair.

4. DISCUSSION

4.1. From directive sentence to distributed instruction. The proposed model extends directive speech-act analysis by showing that algorithmically addressed instruction is normally distributed across a network of microacts. The directive core remains essential, but its success depends on categories that traditional examples often leave in the background: explicit referent management, output formatting, quality criteria, and a visible constraint hierarchy. This does not make prompt discourse linguistically unprecedented. Manuals, recipes, institutional forms, and procedural guidelines have long integrated similar resources. The novelty lies in their concentration within a conversational interface where the same natural-language contribution functions simultaneously as request, task specification, data-selection instruction, and evaluation rubric.

The model also reframes the common opposition between 'good' and 'bad' prompts. A prompt may be grammatically well formed yet pragmatically under-specified; it may be long yet internally contradictory; or it may be minimal but adequate because the relevant referent and task are strongly

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established in prior turns. Prompt adequacy is therefore relational. It depends on the current discourse state, the complexity of the expected output, the risk of divergent interpretations, and the user's acceptance criteria. Requirement completeness is valuable (Ma et al., 2025), but completeness cannot be defined independently of purpose and context.

This relational view explains why prompt patterns should be treated as discourse resources rather than universal formulas. Role assignment, examples, headings, prohibitions, and stepwise decomposition can reduce particular kinds of ambiguity, but their effects depend on task and language. The same surface device may perform different functions: a role label can set expertise, register, audience, or institutional stance; a prohibition can exclude content, control evidence, or prevent a procedure. Linguistic analysis must therefore code function and scope rather than merely count templates.

4.2. Addressivity without anthropomorphis. The functional concept of algorithmic addressee addresses a persistent theoretical tension. On one side, users demonstrably direct utterances to systems, organize turns around their outputs, and use linguistic forms associated with interpersonal address. On the other side, describing the system as if it possessed human comprehension risks confusing successful text generation with human meaning-making. By distinguishing interface addressability, interactional responsiveness, and ontological status, the model allows discourse analysis to examine observable relations without making unsupported psychological claims.

The term also clarifies the difference between channel and participant. A word processor is mainly a tool through which a person produces a document; a prompt-responsive system occupies the sequential position to which the directive is oriented and from which a relevant response is expected. That functional position can influence lexical choices, explicitness, politeness, and repair. Research on social responses to computers has long shown that people apply interpersonal routines to machines even with minimal cues (Nass & Moon, 2000). Contemporary generative interfaces intensify those cues through fluent multi-turn language. The analyst should neither dismiss this interactional reality nor equate it with human personhood.

Accountability remains especially important. In human instruction, responsibility can be attributed to a speaker who issues an unsafe directive or a hearer who refuses a legitimate requirement. In algorithmically mediated action, responsibility is distributed across prompt design, system behavior, training and deployment choices, interface affordances, and user verification. The algorithmic-addressee model is therefore descriptive, not exculpatory: identifying a system as the functional recipient of an instruction does not remove human or institutional accountability for the conditions under which its output is used.

4.3. Grounding as the central interactional problem. The strongest point of convergence between classical pragmatics and current LLM research concerns grounding. Gricean cooperation and common-ground theories assume that participants manage what is mutually available and sufficient for the task (Grice, 1975; Clark & Brennan, 1991). In human-LLM interaction, the surface coherence of a response can create an impression of shared understanding before crucial requirements have been tested. This makes grounding failures difficult to detect early and helps explain why users frequently repair only after inspecting an output.

Recent evidence supports treating clarification as a differentiated phenomenon rather than a single ability. Shaikh et al. (2025) report broad disparities between human and model grounding behavior in conversational datasets; Madge et al. (2025) show that referential ambiguity and task uncertainty do not produce parallel clarification patterns. The proposed model locates these differences within two separate categories: referential anchoring and metadiscursive monitoring/repair. A system may identify a doubtful referent while failing to question an uncertain task procedure, or

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vice versa. Evaluation should therefore ask what kind of uncertainty was available, who initiated clarification, and whether the resulting move repaired the relevant trouble source.

The distinction between repair and refinement adds another layer. User follow-ups are often interpreted as evidence that the original prompt was defective, but requirements can be genuinely emergent. Seeing an output externalizes possible interpretations and enables users to articulate preferences they did not previously formulate. Multi-turn instruction is consequently not always a failure mode. It can be a normal method of collaborative design, even though the collaboration is asymmetrical and the human participant often bears greater responsibility for monitoring alignment.

4.4. Implications for comparative and cross-linguistic research. The model is intended to support comparison across languages without reducing the analysis to translations of English prompt templates. The nine categories provide a tertium comparationis at the functional level. Languages may realize directive force through different combinations of imperative morphology, modal predicates, interrogatives, particles, honorifics, or conditional constructions; they may mark reference through word order, case, agreement, articles, demonstratives, or ellipsis. What should be compared is how a common instructional function is encoded, not which word corresponds to an English keyword.

Cross-lingual politeness research already demonstrates that a surface scale developed for one language cannot automatically be generalized to another (Yin et al., 2024). The same caution applies to explicitness and constraint formulation. A language with rich inflectional morphology may encode relations compactly that English expresses through separate function words; a pro-drop language may omit an addressee or agent without creating the same ambiguity as English omission. Corpus design should therefore use functionally equivalent task scenarios and independently produced instructions in each language, followed by analysis of formal and pragmatic equivalence.

For an English-Uzbek study, for example, the model would permit comparison of English imperative and modal constructions with Uzbek imperative-desiderative forms, modal-predicative units, case marking, converbs, and postpositional structures. Such hypotheses require empirical bilingual data and should not be inferred from the present conceptual review. The contribution here is the analytical map: task, deontic force, reference, context, sequence, constraints, output, interpersonal calibration, and repair can be coded in both languages while their language-specific realizations remain open to investigation.

4.5. Limitations and future research. The study has four limitations. First, its source base is English-dominant, reflecting the current publication landscape in prompt and LLM research. The proposed categories therefore require validation in typologically and culturally diverse languages. Second, the analysis is conceptual and does not report an original interaction corpus; it cannot establish category frequencies, causal effects, or model-specific performance. Third, language-model interfaces and system behavior change rapidly, so interactional tendencies identified in current studies should not be treated as permanent properties of all systems. Fourth, the model privileges text-based instruction and only indirectly addresses multimodal prompts, tool use, and embodied agents.

Future research should construct controlled yet naturalistic corpora in which speakers of different languages formulate instructions for functionally equivalent tasks. Initial prompt-response pairs should be supplemented with full repair trajectories, because isolated prompts cannot reveal how requirements emerge. Coding should distinguish task uncertainty from referential ambiguity, genuine repair from refinement, and linguistic effects from interface or model effects. Inter-coder reliability, version control, and transparent metadata are necessary if results are to support robust comparative conclusions.

A further priority is to investigate how metadiscursive instructions influence grounding behavior. Requests such as 'ask a clarifying question if the task is ambiguous' explicitly assign a conversational

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obligation to the system, but the quality and timing of clarification remain empirical questions. Research should also examine whether users adapt over time by increasing explicitness, modularity, or constraint density, and whether such adaptation transfers across languages or remains shaped by language-specific pragmatic norms.

CONCLUSION

Instructional discourse addressed to a generative language system is neither a wholly new language form nor a simple extension of ordinary command. It preserves the directive and procedural foundations of human instruction while reorganizing them around a computational recipient, an inspectable output, and an asymmetrical process of grounding. The integrative analysis developed in this study identifies nine categorial-pragmatic components: task-intent orientation, directive and deontic force, referential anchoring, context and audience specification, procedural sequencing, constraint architecture, output and quality specification, interpersonal calibration, and metadiscursive monitoring and repair.

These components support two central theoretical claims. First, a prompt is best treated as an instructional macroact composed of functionally distinct microacts rather than as an undifferentiated input string. Second, the algorithmic addressee is a functional discourse role: it is linguistically addressable and sequentially responsive, but the category does not presuppose consciousness or human-like understanding. The interaction becomes analytically complete only when the initial prompt is related to its response and, where necessary, to clarification, repair, refinement, and revised output.

The proposed model offers a foundation for corpus annotation, cross-linguistic comparison, and the analysis of prompt literacy. Its broader implication is that effective human-AI instruction is not reducible to formulaic tricks. It is a form of discourse design in which linguistic choices regulate intention, reference, procedure, limits, interpersonal stance, and the conditions under which a response will count as adequate.

REFERENCES

1. Austin, J. L. (1962). How to do things with words. Clarendon Press.
2. Bender, E. M., & Koller, A. (2020). Climbing towards NLU: On meaning, form, and understanding in the age of data. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (pp. 5185-5198). Association for Computational Linguistics. https://doi.org/10.18653/v1/2020.acl-main.463
3. Brown, P., & Levinson, S. C. (1987). Politeness: Some universals in language usage. Cambridge University Press.
4. Clark, H. H. (1996). Using language. Cambridge University Press.
5. Clark, H. H., & Brennan, S. E. (1991). Grounding in communication. In L. B. Resnick, J. M. Levine, & S. D. Teasley (Eds.), Perspectives on socially shared cognition (pp. 127-149). American Psychological Association. https://doi.org/10.1037/10096-006
6. Clark, H. H., & Schaefer, E. F. (1989). Contributing to discourse. Cognitive Science, 13(2), 259-294. https://doi.org/10.1207/s15516709cog1302_7
7. Elizabeth, M., Lecorvé, G., Rojas Barahona, L. M., & Ochs, M. (2026). Conversational grounding in large language models: Evaluation methods, challenges and future directions. In Proceedings of the 27th Annual Meeting of the Special Interest Group on Discourse and Dialogue (pp. 151-163). Association for Computational Linguistics.
8. Esposito, E. (2022). Artificial communication: How algorithms produce social intelligence. MIT Press.

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

9. Farkas, D. K. (1999). The logical and rhetorical construction of procedural discourse. Technical Communication, 46(1), 42-54.
10. Grice, H. P. (1975). Logic and conversation. In P. Cole & J. L. Morgan (Eds.), Syntax and semantics: Vol. 3. Speech acts (pp. 41-58). Academic Press.
11. Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human-machine communication research agenda. New Media & Society, 22(1), 70-86. https://doi.org/10.1177/1461444819858691
12. Hancock, J. T., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations. Journal of Computer-Mediated Communication, 25(1), 89-100. https://doi.org/10.1093/jcmc/zmz022
13. Herring, S. C. (2004). Computer-mediated discourse analysis: An approach to researching online behavior. In S. A. Barab, R. Kling, & J. H. Gray (Eds.), Designing for virtual communities in the service of learning (pp. 338-376). Cambridge University Press. https://doi.org/10.1017/CBO9780511805080.016
14. Herring, S. C. (2013). Discourse in Web 2.0: Familiar, reconfigured, and emergent. In D. Tannen & A. M. Trester (Eds.), Discourse 2.0: Language and new media (pp. 1-25). Georgetown University Press.
15. Hohenstein, J., Kizilcec, R. F., DiFranzo, D., Aghajari, Z., Mieczkowski, H., Levy, K., Naaman, M., Hancock, J. T., & Jung, M. F. (2023). Artificial intelligence in communication impacts language and social relationships. Scientific Reports, 13, Article 5487. https://doi.org/10.1038/s41598-023-30938-9
16. Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. ACM Computing Surveys, 55(9), 1-35. https://doi.org/10.1145/3560815
17. Longacre, R. E. (1996). The grammar of discourse (2nd ed.). Plenum Press.
18. Lu, A., Zhang, H., Zhang, Y., Wang, X., & Yang, D. (2023). Bounding the capabilities of large language models in open text generation with prompt constraints. In Findings of the Association for Computational Linguistics: EACL 2023 (pp. 1982-2008). Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.findings-eacl.148
19. Ma, Q., Peng, W., Yang, C., Shen, H., Koedinger, K., & Wu, T. (2025). What should we engineer in prompts? Training humans in requirement-driven LLM use. ACM Transactions on Computer-Human Interaction, 32(4), 1-27. https://doi.org/10.1145/3731756
20. Madge, C., Purver, M., & Poesio, M. (2025). Referential ambiguity and clarification requests: Comparing human and LLM behaviour. In Proceedings of the Eighth Workshop on Computational Models of Reference, Anaphora and Coreference (pp. 1-11). Association for Computational Linguistics. https://doi.org/10.18653/v1/2025.crac-1.1