

Alternative-Space Structure Shapes Negation Resolution in Multimodal Generation

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Negation is more difficult to process than affirmation (Clark & Chase, 1974; Carpenter & Just, 1975), but this difficulty is not uniform. Rather than computing a logical complement, negation typically rejects a salient expectation and directs attention toward relevant alternatives (Horn, 1989; Kaup & Dudschig, 2020). Crucially, negation facilitates consideration of an alternative only when the alternative space is sufficiently constrained, either by a conventionalized binary contrast or by the prominence of a likely counterstate (Orenes et al., 2014; Capuano et al., 2023). We use text-to-image generation as a complementary methodological tool to investigate this principle. Unlike sentence comprehension, image generation cannot leave negation underspecified: it must commit to a concrete visual interpretation, making alternative selection directly observable.

Across two preregistered rating experiments, participants evaluated how well AI-generated images matched affirmative and negated prompts. In Experiment 1 ($N = 80$), Stable Diffusion XL generated images from prompts containing binary (e.g., *The shopping basket is not empty*) or multinary predicates (e.g., *The shopping basket does not contain vegetables*). Participants rated sentence-image correspondence on a 6-point scale. Negation reduced image-sentence match overall, but this cost was significantly smaller for binary than for multinary predicates.

Experiment 2 ($N = 99$) tested whether this advantage reflects binary contrast itself or the graded prominence of alternatives. Using minimal copular sentences (e.g., *That is not an onion* vs. *That is not a chair*), we manipulated whether the negated noun had a highly prominent alternative based on cloze norms (Capuano et al., 2023). Images generated with ChatGPT 5.2's image-generation model were evaluated in the same task. Again, negation reduced sentence-image match, but this cost was attenuated when a highly prominent alternative was available, even though all items involved open alternative spaces.

Together, the findings suggest that successful negation resolution depends not simply on the number of possible alternatives but on how strongly linguistic and conceptual structure privilege a counterstate. This constraint can arise categorically through binary contrast structure or gradationally through alternative prominence. The findings converge with psycholinguistic accounts in which negation functions by restricting attention to relevant alternatives rather than computing an exhaustive logical complement. More broadly, multimodal generation provides a hypothesis-generating paradigm for psycholinguistic theories of meaning representation because forced representational commitment makes the consequences of alternative selection directly observable.

References

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Figures and Tables



Figure 1: Experiment 1 - Mean accuracy ratings ($\pm se$) and example items.

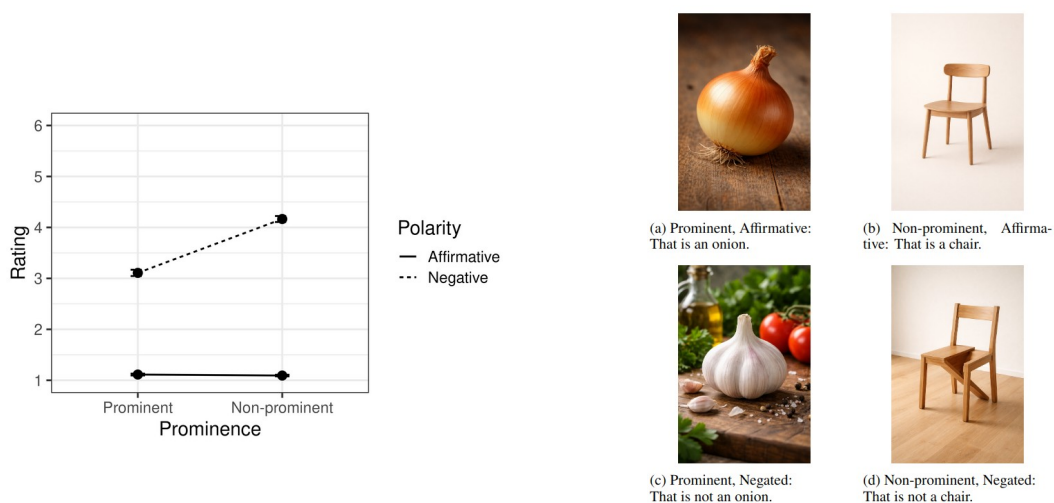


Figure 2: Experiment 2 - Mean accuracy ratings ($\pm se$) and example items.