The Impact of Non-Linear Language on Cognitive Efficiency in Physics Reasoning: A Comparison Between Circular Graphical Language and Linear Text

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1 Introduction

In high school physics education, problem statements are often presented in lengthy linear text. When reading, students must parse sentence structures while simultaneously searching for key conditions and variable relationships before engaging in physics reasoning. This process frequently creates an additional extraneous cognitive load, making it harder to understand the problem and preventing deeper engagement with the concepts of physics. According to Cognitive Load Theory (Sweller, 1988), the capacity of human working memory is limited, and poorly designed representations can consume excessive cognitive resources before problem solving even begins.

This issue led me to wonder: Is there a more intuitive language system that can effectively reduce extraneous load and help students grasp problem statements more quickly? The film *Arrival* provided inspiration through its depiction of a non-linear alien language. The Sapir–Whorf Hypothesis suggests that language structures may influence patterns of thought. If the linear nature of human language constrains our reasoning, then designing a "non-linear visual language" might improve efficiency in solving physics problems.

To test this idea, this study introduces a Circular Language, which represents physics problems as graphical structures composed of nodes and connections. The research aims to examine:
(1) whether Circular Language can reduce extraneous cognitive load and improve problem-solving efficiency
(2) whether the effectiveness varies with problem difficulty

2 Literature Review

2.1 Linear vs. Non-Linear Language

Linear language arranges information sequentially, requiring readers to follow a fixed path (e.g., written or spoken language). Physics problems in text form are typical examples. For instance: "A 2 kg object falls freely from a height of 10 m. Neglect air resistance. Calculate its velocity upon hitting the ground." In this form, students must read word by word, then extract and integrate the conditions themselves.

By contrast, non-linear language allows multiple dimensions of information to be presented simultaneously. Visual cues such as diagrams, spatial layouts, or color markers enable faster recognition of problem elements. The proposed Circular Language is one such system: problem conditions (e.g., mass, height, motion state, target quantity) are represented as nodes, with arrows or links showing relationships. Theoretically, this reduces the burden of information search and allows students to focus on reasoning.

2.2 Linguistic Relativity

The Sapir–Whorf Hypothesis suggests that language influences human cognition. While the strong form of linguistic determinism has been debated, the weaker form of linguistic relativity has empirical support (e.g., Boroditsky, 2001). Differences in language structure can shape thought; therefore, transforming physics problems from linear text into a circular structure could lead to measurable differences in cognitive efficiency.

2.3 Cognitive Load Theory

Cognitive Load Theory (Sweller, 1988) distinguishes three types of load: intrinsic (material complexity), extraneous (representation and instructional design), and germane (schema-building effort). If a representation reduces the extraneous load, more resources can be allocated to understanding and reasoning. Miller's (1956) work highlights working memory limits, while Just and Carpenter (1992) show that response time can indicate cognitive load. Consequently, this study uses response time, accuracy, and stability as objective indicators to compare linear and non-linear representations.

3 Methodology

3.1 Research Subjects

To ensure fairness in comparing representations, this study uses an AI model (OpenAI's GPT-3.5-turbo) as the problem solver, accessed via API. This choice supports (1) consistent reasoning, (2) repeated testing under identical conditions, and (3) a focus on representation effects rather than individual differences.

3.2 Research Goals

1. Design a non-linear Circular Language to represent physics problems.
2. Develop a bank of 30 high-school physics problems across three difficulty levels (easy, medium, hard) in linear text.
3. Convert all 30 problems into Circular Language.
4. Measure AI performance using response time, accuracy, and stability for both formats.
5. Compare performance differences across the two representations.

3.3 Experimental Design

3.3.1 Circular Language Design

Inspired by *Arrival*, the representation uses three concentric rings:

- **Inner ring:** target physical quantity (e.g., velocity).

- **Middle ring:** solving conditions (e.g., $t = 3\,\text{s}$).
- **Outer ring (A/B/C):**
  A. constants (e.g., $m = 5\,\text{kg}$)
  B. variables (e.g., $v = t^2 + 2t + 7$)
  C. boundaries (e.g., $t = 0, v = 0$)

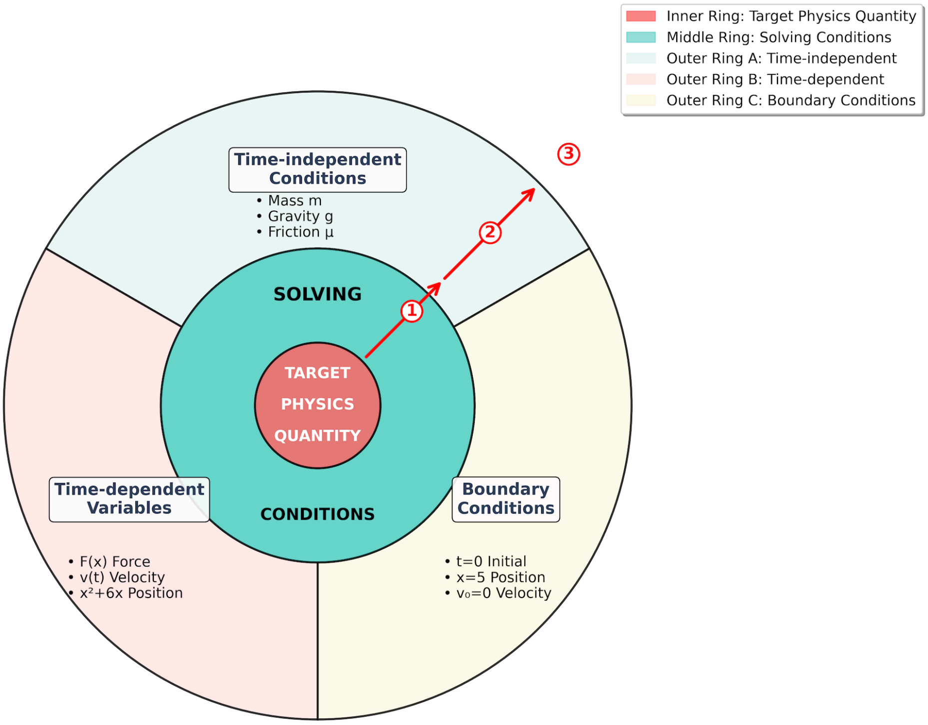

Figure 1: Schematic of the Circular (concentric) Language representation.

3.3.2 Source of Physics Problems

A custom problem bank of 30 items was designed and verified, distributed across three levels:

- **Easy (Problems 1–10):** basic kinematics and Newton's laws (uniform acceleration, free fall, simple energy conservation); typically one-step solutions; tests low-load performance.
- **Medium (Problems 11–20):** multi-step reasoning (elastic collisions, oscillations, thermodynamic energy transfer); tests moderate-load performance.
- **Hard (Problems 21–30):** rigid-body rotation, coupled systems, complex thermodynamic processes; extended derivations and multiple formulas; tests high-load performance.

All problems yield a single numerical answer to avoid ambiguity.

3.3.3 Comparison of Problem Formats

To illustrate the difference between the two representations, consider the following problem (Problem 1):

Linear text format:

"Jessica drives her car from home to school, covering a distance of 120 km. The trip takes exactly 2 hours due to morning traffic. Calculate Jessica's average speed."

In the linear format, the problem is presented as a continuous sentence. Students must read word by word, identify the numerical values (120 km, 2 hours), and then recall the relevant formula for average speed. This process requires both language parsing and information extraction before the actual reasoning step can begin.

Circular Language format:

Target: speed
Condition: average
Outer-A (constants): distance = 120 km, time = 2 h

In the circular format, the same problem is represented visually with nodes and rings. The target physical quantity (speed) is placed at the center, while relevant conditions and constants are explicitly organized around it. This structure eliminates the need to parse sentences, allowing direct access to the information needed for computation.

Linear text demands sequential reading and interpretation, whereas the circular format externalizes relationships between quantities, reducing extraneous cognitive load. This makes it easier for the solver to focus on applying physics reasoning rather than spending effort on extracting conditions from text.

3.3.4 Cognitive Load Indicators

1. **Response time(RT):** Following Just and Carpenter (1992), shorter RT indicates lower load and faster processing. RTs were baseline-corrected using a standardized "hello" prompt (five trials averaged) to remove system latency.
2. **Accuracy:** Based on Chandler and Sweller (1991), high load increases error rates. AI answers were compared against standard solutions with $\pm 5\%$ tolerance for numerical precision.
3. **Stability:** Following Kahneman (1973), high load increases variability. Each problem was tested three times per format; the coefficient of variation (CV) was computed. Stability was defined as Stability $= \max(0, 1 - \text{CV})$ and graded: High (0.8–1.0), Moderate (0.6–0.8), Low (0.4–0.6), Unstable (0.0–0.4).

3.4 Testing Procedure

A fully randomized design was adopted. Each of the 30 problems was tested in both formats, with three repetitions each (total $30 \times 2 \times 3 = 180$ trials). A 10-second interval between tests minimized interference. For each problem, average values across repetitions were recorded as representative data. Baseline correction and full randomization of both problem order and representation order were applied.

4 Results and Analyses

4.1 Detailed Results by Difficulty

Table 1: Performance comparison for easy problems (Problems 1–10)

ID	Linear Time (sec)	Non-linear Time (sec)	Linear Acc. (%)	Non-linear Acc. (%)	Speed Impr. (%)	Acc. Impr. (%)
1	0.034	0.117	100.0	100.0	-240.2	+0.0
2	0.078	0.085	100.0	33.3	-9.8	-66.7
3	0.063	0.018	100.0	33.3	+71.8	-66.7
4	0.168	0.378	0.0	66.7	-125.0	+66.7
5	0.518	0.057	100.0	100.0	+89.1	+0.0
6	0.039	0.043	0.0	66.7	-9.2	+66.7
7	1.196	0.133	100.0	100.0	+88.9	+0.0
8	0.024	0.471	0.0	100.0	-1846.2	+100.0
9	0.131	0.394	100.0	100.0	-202.1	+0.0
10	0.022	0.021	0.0	0.0	+1.8	+0.0

Table 2: Performance comparison for medium problems (Problems 11–20)

ID	Linear Time (sec)	Non-linear Time (sec)	Linear Acc. (%)	Non-linear Acc. (%)	Speed Impr. (%)	Acc. Impr. (%)
11	2.256	1.407	100.0	100.0	+37.7	+0.0
12	2.844	1.273	33.3	100.0	+55.3	+66.7
13	1.929	1.466	100.0	100.0	+24.0	+0.0
14	1.490	1.499	66.7	33.3	-0.6	-33.3
15	1.472	1.023	66.7	100.0	+30.5	+33.3
16	3.754	1.304	0.0	100.0	+65.3	+100.0
17	1.288	1.008	0.0	0.0	+21.7	+0.0
18	3.653	1.810	0.0	33.3	+50.4	+33.3
19	0.926	0.922	0.0	100.0	+0.5	+100.0
20	1.640	0.578	0.0	0.0	+64.8	+0.0

Table 3: Performance comparison for hard problems (Problems 21–30)

ID	Linear Time (sec)	Non-linear Time (sec)	Linear Acc. (%)	Non-linear Acc. (%)	Speed Impr. (%)	Acc. Impr. (%)
21	4.392	1.853	0.0	100.0	+57.8	+100.0
22	3.738	1.323	100.0	100.0	+64.6	+0.0
23	3.743	1.827	0.0	0.0	+51.2	+0.0
24	4.228	3.049	0.0	0.0	+27.9	+0.0
25	3.036	2.686	0.0	100.0	+11.5	+100.0
26	2.260	1.949	0.0	0.0	+13.8	+0.0
27	3.704	3.450	100.0	100.0	+6.9	+0.0
28	2.420	1.757	100.0	100.0	+27.4	+0.0
29	5.851	2.855	0.0	0.0	+51.2	+0.0
30	3.807	2.323	66.7	100.0	+39.0	+33.3

4.2 Comparative Plots: Time, Accuracy, and Stability

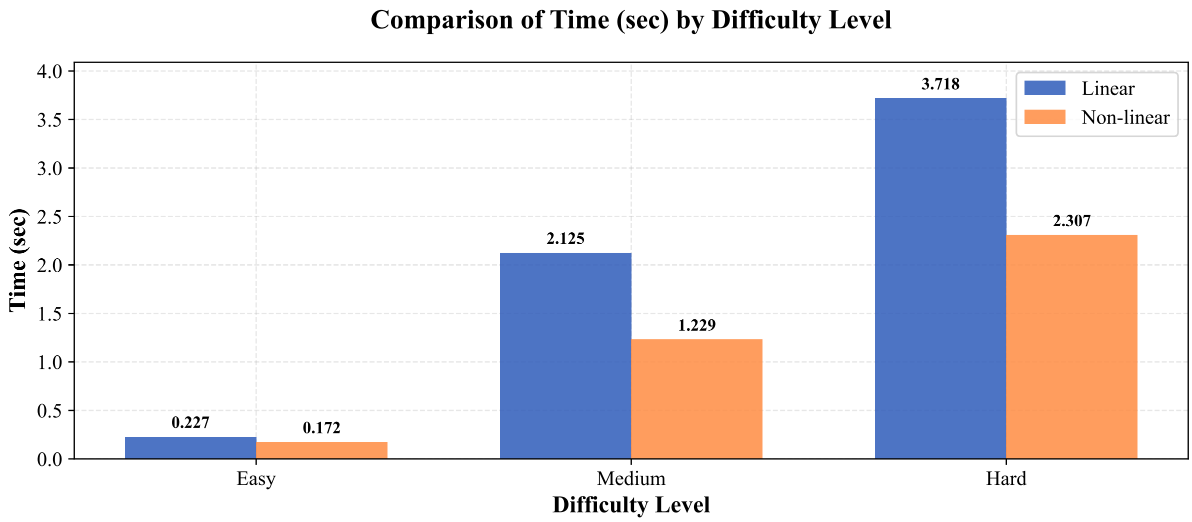

Figure 2: Comparison of Time (sec) by Difficulty Level

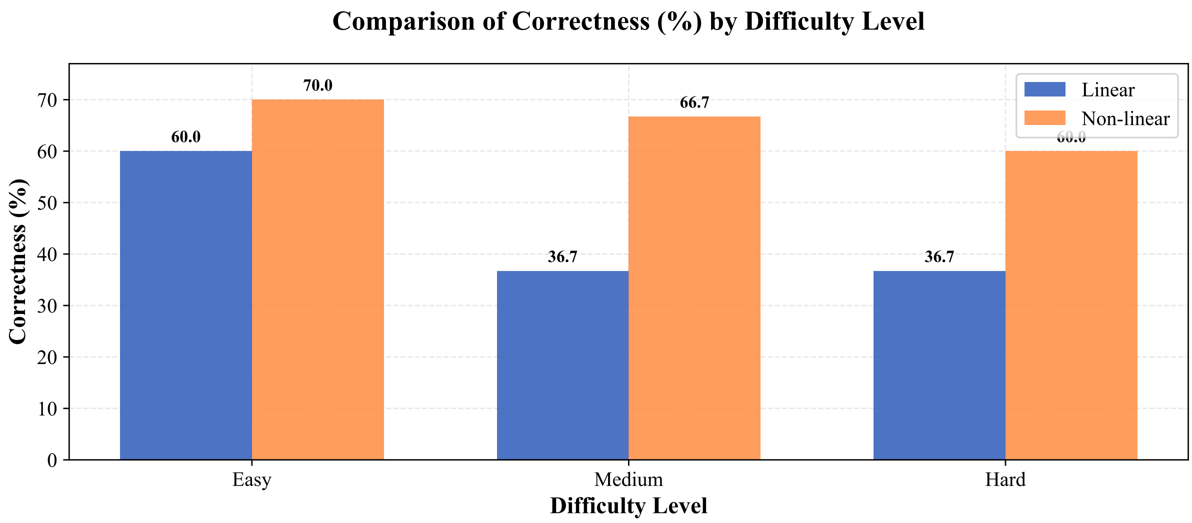

Figure 3: Comparison of Correctness (%) by Difficulty Level

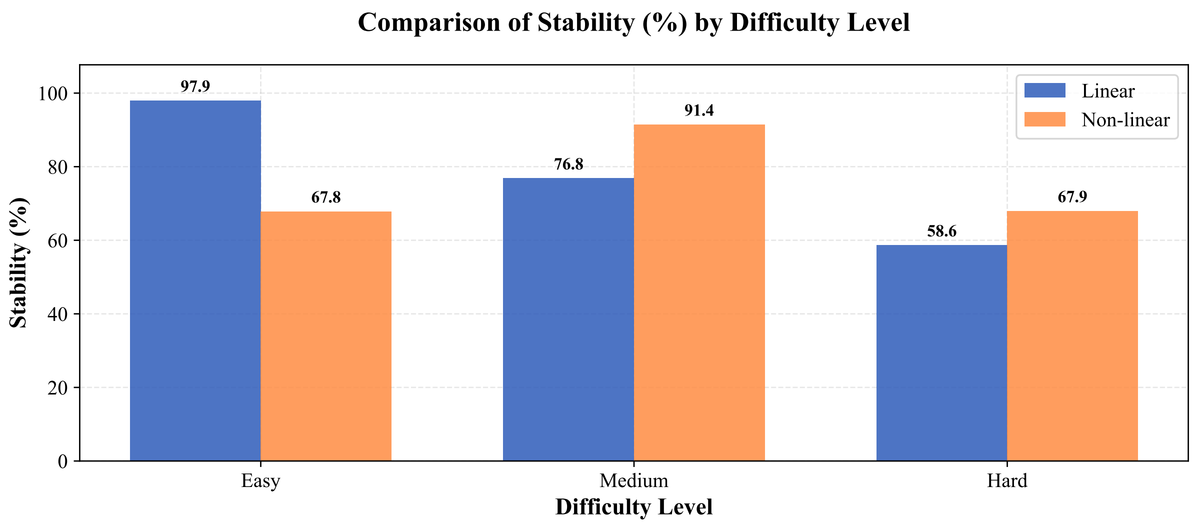

Figure 4: Comparison of Stability (%) by Difficulty Level

4.3 Comprehensive Analysis

The comparative results demonstrate that problem representation significantly affects cognitive efficiency. For easy problems, the linear text format often yielded higher stability and accuracy, indicating that the added structure of Circular Language may introduce unnecessary complexity when intrinsic load is low. Nonetheless, isolated cases showed that Circular Language could accelerate information retrieval.

For medium problems, Circular Language consistently outperformed linear text in both response time and accuracy. Multi-step reasoning tasks benefited from explicit visual organization, which reduced extraneous load by externalizing relationships among variables. This suggests that non-linear representations are especially advantageous when intrinsic complexity begins to increase.

For hard problems, Circular Language provided the clearest advantage. Response times were reduced by approximately 40–60%, and accuracy improved on multiple items. Although some problems remained unsolved due to their inherent difficulty, the overall pattern confirms that non-linear representation mitigates cognitive strain in high-load conditions.

Taken together, these findings support Cognitive Load Theory that when extraneous load is reduced, more cognitive resources can be allocated to reasoning. The Circular Language appears most effective for problems of moderate to high complexity, while linear text remains sufficient or even preferable for simple tasks.

5 Conclusion

This study introduced a non-linear representation of physics problems and evaluated its effectiveness against linear text using an AI problem solver. The results indicate that Circular Language improves efficiency by reducing response time and increasing accuracy, particularly for medium and hard problems, while maintaining comparable stability. These outcomes validate the hypothesis that representation design can reduce extraneous cognitive load and facilitate more effective reasoning.

Thus, the Circular Language not only answers the initial questions but also opens the door to new possibilities in science education. If language can shape thought, then carefully designed representations can shape how students learn. By presenting physics problems in a format that mirrors reasoning structures rather than grammatical ones, we may help learners engage more deeply with concepts instead of getting lost in sentences. Future research should test this approach with human students across different proficiency levels and explore whether non-linear visual languages can support learning in other STEM domains as well.

References

Boroditsky, L. (2001). Does language shape thought?: Mandarin and English speakers' conceptions of time. *Cognitive Psychology, 43*(1), 1–22. https://doi.org/10.1006/cogp.2001.0749

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction, 8*(4), 293–332. https://doi.org/10.1207/s1532690xci0804_2

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Evans, N., & Levinson, S. C. (2009). The myth of language universals: Language diversity and its importance for cognitive science. *Behavioral and Brain Sciences, 32*(5), 429–448. https://doi.org/10.1017/S0140525X0999094X

Just, M. A., & Carpenter, P. A. (1992). A capacity theory of comprehension: Individual differences in working memory. *Psychological Review, 99*(1), 122–149. https://doi.org/10.1037/0033-295X.99.1.122

Kahneman, D. (1973). *Attention and effort*. Prentice-Hall.

Lieberman, P. (2006). *Toward an evolutionary biology of language*. Harvard University Press.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63*(2), 81–97. https://doi.org/10.1037/h0043158

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Appendices

1. Code Documentation
   The complete source code for all experiments is available at: https://github.com/Hungyu8484/Linguistic-Project/blob/main/code_documentation.html
2. Experimental Data
   The detailed experimental results and statistical analysis are available at: https://github.com/Hungyu8484/Linguistic-Project/blob/main/data_documentation.html