Constructing Meaning through AI Prompts: A Cognitive Discourse Analysis of Student Strategies in Scientific Article Writing Comprehensive Research Analysis

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INTRODUCTION

1. Students struggle with effective AI prompt construction for academic writing
2. Current student behavior patterns Use ChatGPT for idea generation → build own arguments → edit/revise (Levine, 2024) → No cognitive framework exists that explains HOW students construct effective prompts
3. Zero assessment methods for prompt engineering competency (Lee & Palmer, 2025)
4. Map cognitive strategies students use when constructing ChatGPT prompts for scientific articles

LITERATURE REVIEW

1. Cognitive Discourse Analysis

Cognitive Discourse Analysis (CODA) methodology analyzes verbal protocols and unconstrained language use to access mental representations and high-level cognitive processes (Tenbrink, 2015; Tenbrink, 2020)

2. AI-Assisted Academic Writing Research

Students with high AI literacy employ collaborative approaches, actively accepting GenAI suggestions and involving AI in planning processes, while low literacy students interact to a lesser extent with more independent, student-driven approaches (Kim et al., 2025)

3. Prompt in Educational Contexts

Well-designed prompts have transformative potential for GenAI interactions in higher education, requiring systematic development through structured frameworks rather than intuitive approaches (Lee & Palmer, 2025)

4. Prompt in Scientific Article

Brown et al. (2020) define prompts as instructions that guide language model output without requiring additional fine-tuning, while Wei et al. (2022) developed the concept of chain-of-thought prompting that enables step-by-step reasoning in academic writing. In academic contexts, prompts are classified into three main categories: structural prompts that follow the IMRAD format (Zhao et al., 2023), methodological prompts that focus on research aspects (Liu et al., 2023), and argumentative prompts that encourage evidence-based reasoning (Ouyang et al., 2022). Principles of effective prompt design include specificity and clarity (Wang et al., 2023), contextual relevance that integrates domain-specific context (Chowdhery et al., 2022), and iterative refinement based on evaluation feedback (Min et al., 2022).

METHOD

Data Collection Steps

1 In-Depth Interviews
50 students
60-90 min
Prompt strategies

2 Observation
Real-time
Screen recording
Behavior patterns

3 Document Analysis
Student articles
Quality assessment
Effectiveness

4 Questionnaires
Students &
Supervisors
Perceptions

5 Cognitive Analysis
Transcript analysis
CBPM patterns
Strategies

Triangulation Framework

DATA TRIANGULATION
Students, Supervisors,
AI-generated texts

METHOD TRIANGULATION
Interviews, Observations,
Documents, Surveys

VALIDITY ENHANCEMENT through TRIANGULATION

INVESTIGATOR
Multiple researchers
Independent analysis

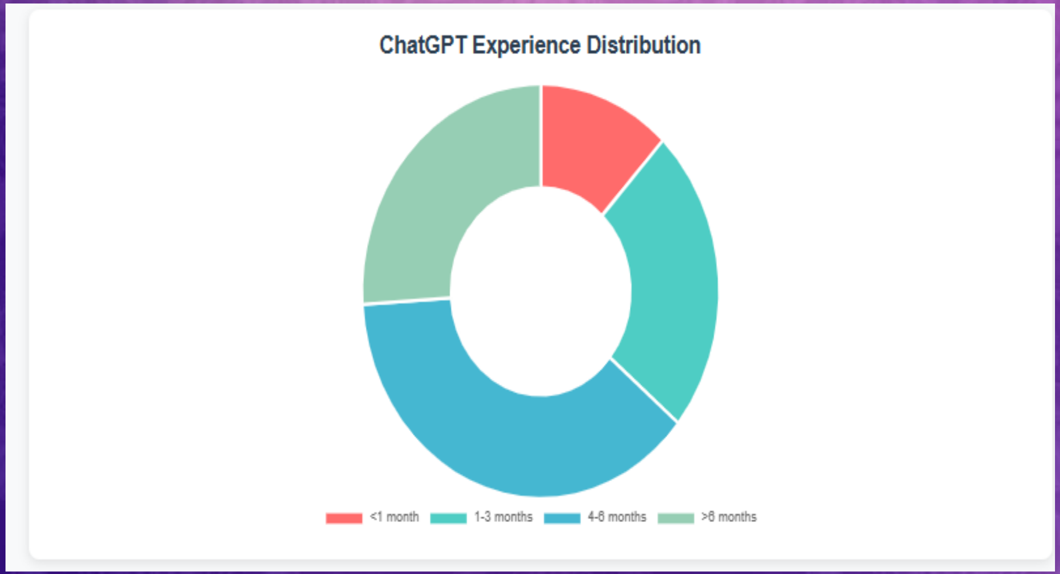
THEORETICAL TRIANGULATION
CODA + Prompt Engineering

Analytical Process Flow

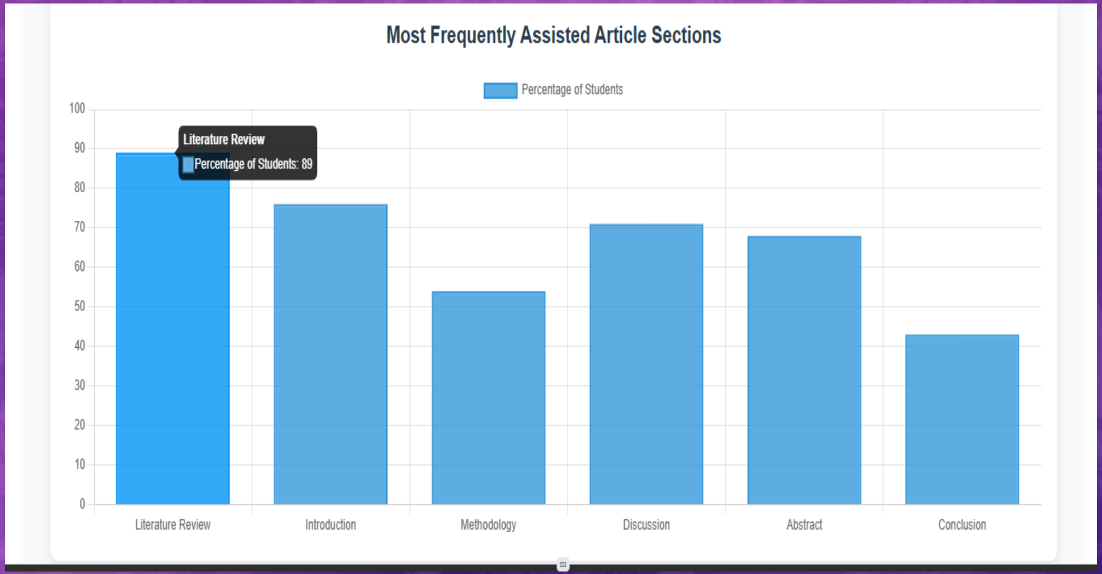
Collection → Transcription → Coding →
CBPM Patterns → Validation → Guidelines

FINDING AND DISCUSSION

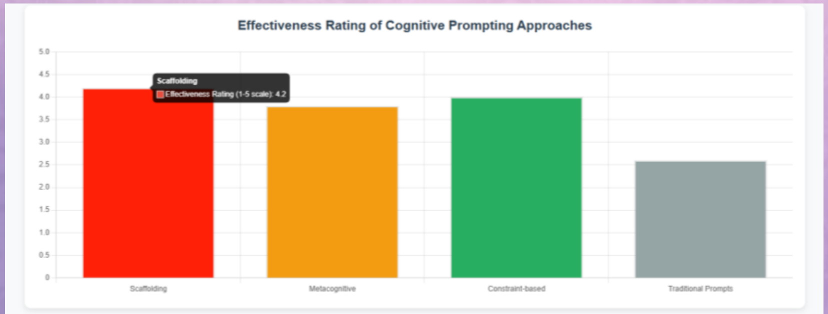
1. ChatGPT Experience Distribution

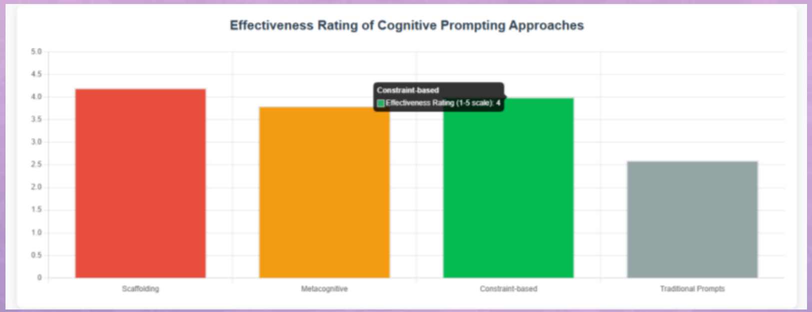


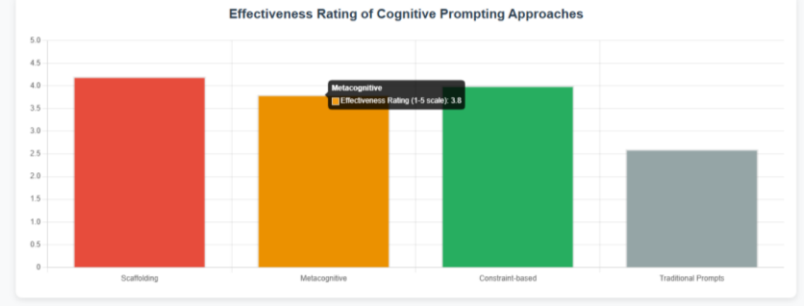
2. Strategic AI Integration in Academic Writing

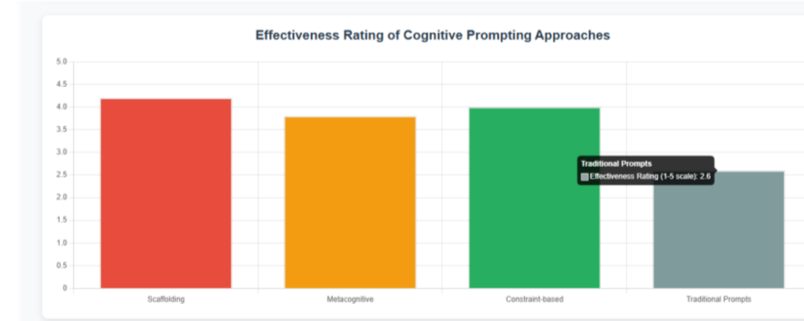


3. Cognitive Prompting Strategies & Effectiveness

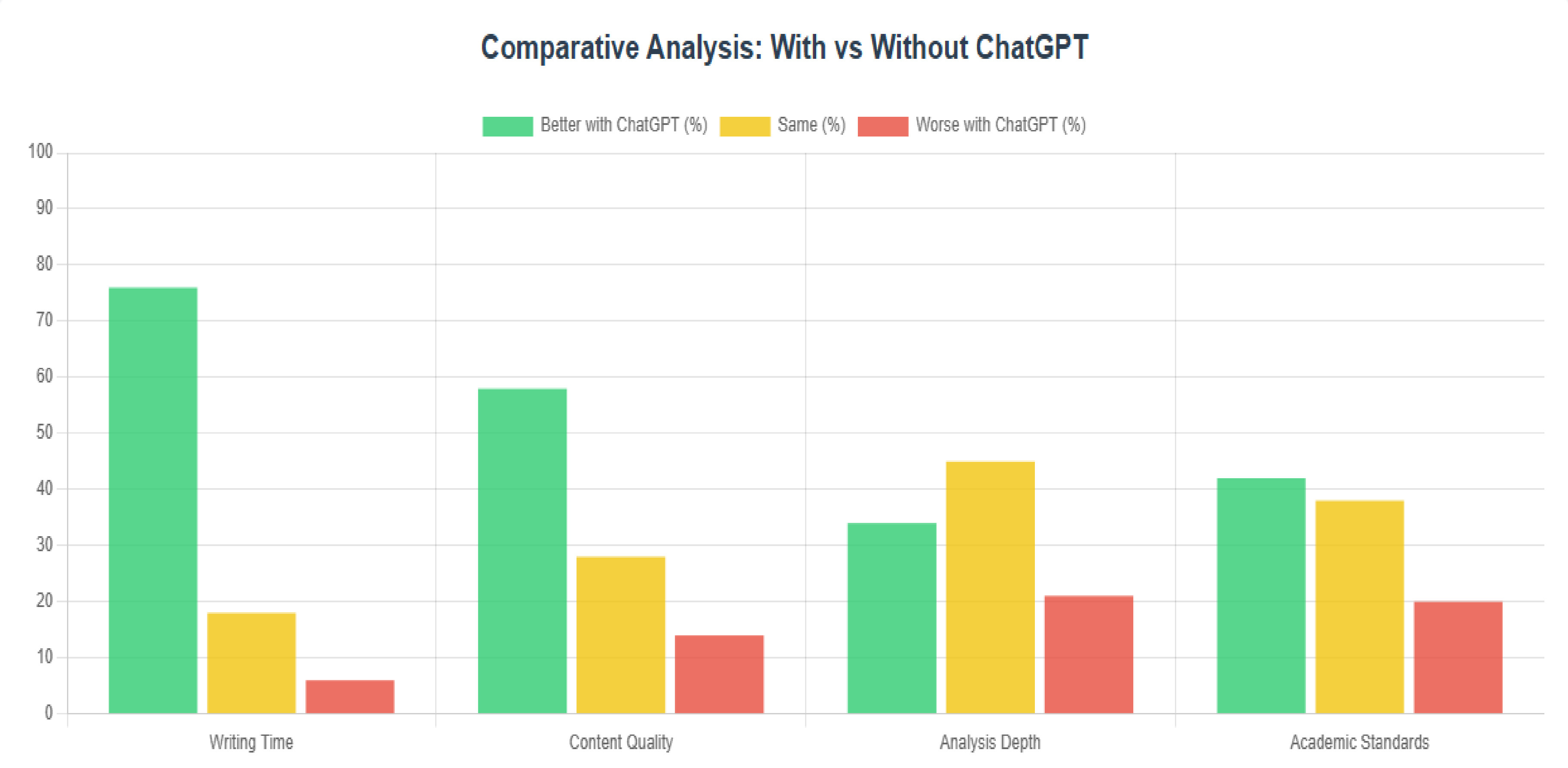








4. Quality Outcomes & Academic Standards



Cognitive-based prompting strategies demonstrate significant impact on academic discourse construction through AI-mediated interaction.

Results support integration of Cognitive Load Theory, Metacognitive Theory, and Critical Discourse Analysis in AI-assisted academic writing contexts.

Educational institutions should implement cognitive-based prompting frameworks to optimize AI-human collaborative learning outcomes.

CONCLUSION

1. Advanced prompting strategies including contextual, scaffolding, and constraint-based

approaches significantly outperform basic prompting methods in AI-assisted scientific writing.

2. High student adoption with strategic focus on literature review and introduction sections, requiring extensive revision indicating active human-AI partnership rather than passive dependency.

3. Proves most critical factor in AI-assisted writing effectiveness, supported by improved knowledge organization, discourse adherence, and iterative construction processes.

4. Demonstrates substantial time efficiency gains, moderate content improvement, and better academic standards compliance, despite persistent challenges in generic output and reference accuracy.

5. Structured AI literacy frameworks, prompt engineering competencies, and metacognitive training essential for optimal human-AI collaboration in academic contexts.

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