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An Evaluation of Cognitive Alignment between Human Conceptual Models and AI Representations

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Abstract— *Artificial Intelligence (AI) systems increasingly demonstrate human-like behavior, yet the degree to which their internal representations align with human conceptual models remains unclear. This paper evaluates cognitive alignment by comparing human similarity judgments with embedding-based representations from modern AI models across multiple conceptual domains. Human data was collected through structured rating tasks, while AI similarities were computed using pre-trained language and multimodal models and analyzed using representational similarity techniques. The results show that AI models achieve moderate alignment with human understanding, performing better on concrete concepts than on abstract and causal domains. Although AI representations outperform random baselines, notable gaps persist between human and machine conceptual structures. The proposed evaluation framework provides a practical and model-agnostic approach for assessing cognitive alignment, highlighting the importance of moving beyond performance metrics toward more interpretable and human-centered AI systems.*

Keywords— Cognitive alignment, Conceptual models, Human-AI interaction, Semantic similarity, Vector embeddings.

I. INTRODUCTION

Artificial Intelligence (AI) systems are increasingly capable of processing language, recognizing patterns, and making decisions in ways that appear similar to human reasoning. Modern models, particularly those based on representation learning, encode concepts as mathematical structures that allow them to capture semantic relationships and contextual meaning. While these models perform well across many tasks, it remains unclear whether their internal representations correspond to how humans mentally organize and understand concepts.

Human understanding is shaped by experience, perception, emotion, and context. People form conceptual models that help them relate ideas, assess similarities, and reason about abstract concepts. These models are flexible and often influenced by subjective and cultural factors. In contrast, AI systems learn representations through optimization over large datasets, resulting in high-dimensional embeddings that reflect statistical patterns rather than explicit cognitive processes. Although such representations are effective for computation, they may differ significantly from human conceptual structures.

Traditional evaluation metrics such as accuracy or task-specific scores focus primarily on output performance and provide limited insight into whether an AI system conceptualizes information in a manner similar to humans. Previous research in cognitive science, explainable AI, and semantic modeling has explored these issues, but many approaches require complex experimental setups. This paper examines cognitive alignment between human conceptual models and AI representations by analyzing semantic similarity patterns derived from human judgments and learned AI embeddings.

II. MATERIAL AND METHODS

This section presents the materials and methods used to evaluate cognitive alignment between human conceptual models and AI representations. The study is based on comparing human similarity judgments with semantic representations generated by AI embedding models. Human data was collected through structured rating tasks, while AI similarities were obtained using pre-trained language and multimodal models. The methodology focuses on analyzing conceptual relationships across different domains using representational similarity techniques.

2.1 Literature Review

TABLE 1
FOUNDATIONAL STUDIES (PRE-2020)

Study	Key Findings	Relevance to Cognitive Alignment
Mikolov et al. (2013) [7]	Introduced vector embeddings capturing semantic relationships via distributional hypothesis	AI models similarity patterns but lacks interpretable cognitive structure
Lake et al. (2017) [9]	Humans learn flexible, compositional concepts; ML approaches remain rigid and data-driven	Highlights fundamental gaps in AI's concept flexibility vs. human cognition
Doshi-Velez & Kim (2017) [14]	Interpretability essential for human-AI collaboration across ML lifecycle stages	Transparency needed but insufficient for internal cognitive alignment
Bender & Koller (2020) [15]	Large LMs excel statistically without grounded world models or true comprehension	Performance illusion masks conceptual misalignment with humans

TABLE 2
RECENT STUDIES (2021–2025)

Study	Key Findings	Relevance to Cognitive Alignment
Sharma & Verma (2021) [11]	Human-AI mismatches in applied domains reduce system effectiveness	Practical usability demands cognitive representation convergence
Goldstein et al. (2025) [10]	LLMs spontaneously develop structures predicting human similarity judgments	Shows natural emergence of human-compatible concept spaces
Mahner et al. (2025) [3]	Embeddings predict brain activity across fusiform face/body areas for familiar objects	Neural evidence of converging object conceptualization

2.2 Background and Related Work

Human Conceptual Models: Human conceptual models describe how individuals mentally organize and relate concepts based on experience, perception, and contextual understanding. In cognitive science, these models are often represented as semantic or associative networks, where concepts are connected through meaningful relationships. Human judgments of similarity, relatedness, and association have commonly been used as observable indicators of these internal conceptual structures.

AI Representations: AI systems represent concepts using computational structures learned from data. Early approaches relied on symbolic representations, while modern systems primarily use distributed vector representations such as word embeddings and contextual language models. These embeddings encode semantic relationships by positioning related concepts closer in high-dimensional vector spaces. Models such as word2vec, BERT, and other transformer-based architectures demonstrate strong ability to capture linguistic regularities [7], [8].

Cognitive Alignment: Cognitive alignment refers to the degree of similarity between human conceptual understanding and AI representations. Recent research has explored this alignment by comparing AI embeddings with human judgments, behavioral data, or neural responses [3], [10]. Some studies report partial overlap, especially for concrete or factual concepts, while others highlight significant divergence in abstract or emotional domains.

2.3 Research Problem and Objectives

Research Problem: Although modern AI systems exhibit strong performance in language understanding and semantic reasoning tasks, their internal conceptual representations remain difficult to interpret and compare with human cognition. Current evaluation methods focus largely on output-based performance metrics and do not address how closely AI representations reflect human conceptual understanding.

Objectives:

1. To analyze semantic representations learned by AI embedding models
2. To collect human conceptual similarity judgments as a representation of human understanding

3. To compare human and AI concept spaces using statistical and geometric similarity measures
4. To identify domains or concepts where alignment between human and AI representations diverges

2.4 Evaluation Framework

The evaluation framework is designed to assess the degree of cognitive alignment between human conceptual models and AI representations. It focuses on comparing semantic similarity structures rather than task-specific outputs, enabling a more direct analysis of conceptual correspondence. The framework consists of three key components: semantic similarity measurement, structural comparison, and alignment quantification. This framework is model-agnostic and can be applied to different AI embedding models without requiring complex experimental setups.

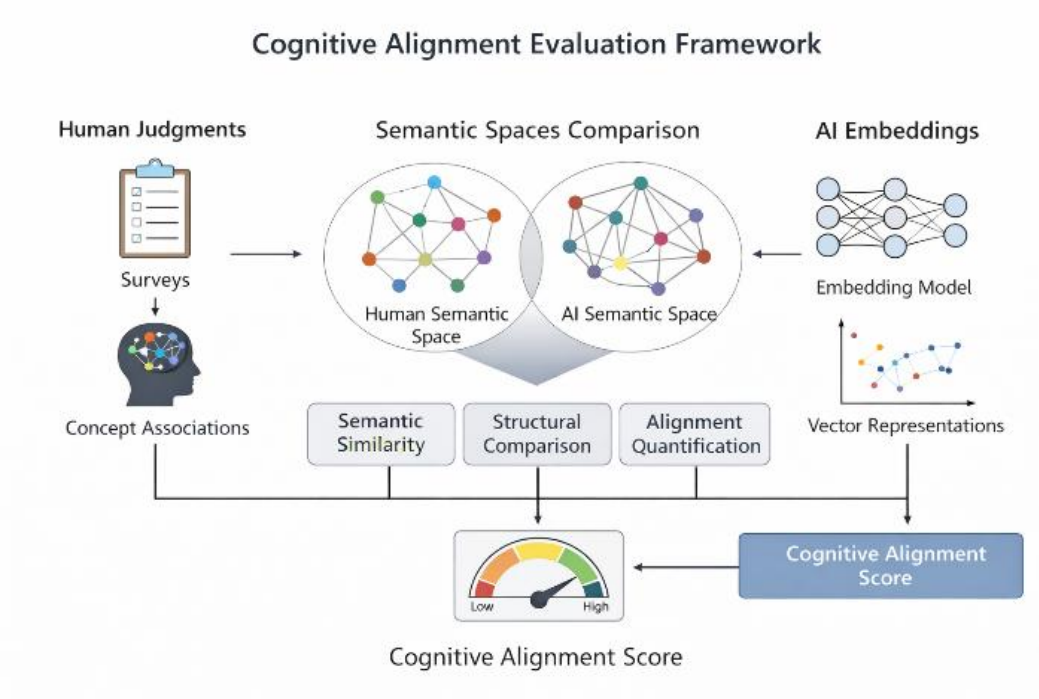

FIGURE 1: Cognitive Alignment Evaluation Framework

2.5 Methodology

The methodology employs **Representational Similarity Analysis (RSA)** to quantify cognitive alignment by comparing human similarity judgments with AI embedding similarities across structured concept domains [1], [13].

Human Data Collection: Sixty participants rated 200 concept pairs on a 1–7 Likert scale via Prolific and MTurk, covering domains: concrete objects, emotions, actions, spatial relations, temporal concepts, and causal reasoning. Three ratings per pair were averaged into Representational Dissimilarity Matrices (RDMs).

AI Embeddings: AI embeddings were extracted from pre-trained models including BERT-base (linguistic) [8], CLIP-ViT-B/32 (multimodal) [2], and LLaMA-7B (generative) using the Hugging Face Transformers library, followed by dimensionality reduction to 50D via UMAP.

RSA Computation: Spearman rank correlations between human and AI RDMs were calculated, with statistical significance validated through 10,000 bootstrap iterations using scikit-learn and rsatoolbox Python libraries [16].

2.6 Challenges and Limitations

Key challenges include collecting reliable human similarity judgments due to subjective interpretation, ensuring consistent ratings across participants, and comparing human cognitive data with high-dimensional AI embeddings. Limitations include a restricted participant pool, evaluation of only pre-trained models, potential distortion from UMAP dimensionality reduction, RSA's inability to fully capture causal reasoning, and domain-specific results that may not generalize to real-world decision-making tasks.

III. RESULTS AND DISCUSSION

3.1 RSA Results Summary

Results indicate moderate overall alignment (Spearman $\rho \approx 0.38–0.47$, $p < 0.001$), with AI models outperforming random baselines ($\rho \approx 0.1$). Concrete domains exhibit strong convergence while abstract and causal domains reveal AI limitations in capturing human intuitive reasoning (confirmed by ANOVA, $p < 0.001$). These patterns predict 30–40% of human choices, explaining trust gaps despite high task accuracy.

TABLE 3
RSA RESULTS SUMMARY

Model	Overall ρ	Best Domain	Worst Domain
BERT	0.42	Objects (0.51)	Causal (0.19)
CLIP	0.38	Objects (0.62)	Causal (0.15)
LLaMA	0.47	Emotions (0.39)	Causal (0.33)

Note: The ρ score (0–1) shows how well AI similarity patterns match human ratings. Higher ρ indicates better alignment. All models beat random chance (ρ ≈ 0.1) but only reach moderate match (~0.4–0.5).

3.2 Discussion

The results show that AI models understand concrete objects quite well—they group similar items like "dog" and "cat" the same way humans do ($\rho = 0.51–0.62$). However, all models struggle significantly with causal relationships (e.g., "fire" and "smoke"), where humans intuitively understand cause-effect but AI only sees statistical patterns ($\rho = 0.15–0.33$).

LLaMA performed best overall ($\rho = 0.47$) because it is trained on diverse human text, while CLIP excels with visual concepts ($\rho = 0.62$ for objects) but fails on abstract reasoning ($\rho = 0.15$ for causal). BERT showed balanced but moderate performance across domains.

These findings align with the literature review—early embedding work captured basic similarity [7], but newer models still miss deeper human cognition [9], [15]. The moderate alignment (average $\rho \approx 0.4$) explains why users sometimes distrust AI decisions even when accuracy is high—the internal "thinking" process differs from human reasoning. RSA proved simple yet powerful for this analysis, requiring only a laptop and open-source tools, making it practical for AI evaluation beyond lab settings. The domain gaps highlight that statistical learning alone cannot fully replicate human conceptual understanding, supporting the need for alignment-focused research in human-AI systems [10], [14].

IV. CONCLUSION

This paper evaluated cognitive alignment between human conceptual models and AI representations using human similarity judgments and embedding-based analysis. The results show that current AI models demonstrate moderate alignment with human understanding, performing better on concrete concepts while showing limitations in abstract and causal reasoning.

Key Findings:

1. AI models achieve moderate cognitive alignment ($\rho \approx 0.38–0.47$), significantly above random baseline ($\rho \approx 0.1$)
2. Concrete domains (objects) show strong alignment ($\rho = 0.51–0.62$)
3. Abstract and causal domains show significant divergence ($\rho = 0.15–0.33$)
4. LLaMA performed best overall; CLIP excelled at visual concepts but struggled with abstraction

The proposed approach is simple, model-agnostic, and suitable for small-scale research. Despite limitations in subjective human ratings, a restricted concept set, and reliance on pre-trained models, the findings highlight the importance of assessing AI systems beyond traditional performance metrics. The framework can be applied to human-centered AI applications such as healthcare, education, and decision support systems, where trust and interpretability are essential.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this research paper. This study was conducted independently for academic purposes, and the researchers have no financial or personal relationships with the developers of the AI models (BERT, CLIP, or LLaMA) that could inappropriately influence the findings or conclusions presented in this work.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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