

# The potential – and the pitfalls – of using pre-trained language models as cognitive science theories

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## Abstract

Many studies have evaluated the cognitive alignment of Pre-trained Language Models (PLMs), i.e., their correspondence to adult performance across a range of cognitive domains. Recently, the focus has expanded to the developmental alignment of these models: identifying phases during training where improvements in model performance track improvements in children’s thinking over development. However, there are many challenges to the use of PLMs as cognitive science theories, including different architectures, different training data modalities and scales, and limited model interpretability. In this paper, we distill lessons learned from treating PLMs, not as engineering artifacts but as cognitive science and developmental science models. We review assumptions used by researchers to map measures of PLM performance to measures of human performance. We identify potential pitfalls of this approach to understanding human thinking, and we end by enumerating criteria for using PLMs as credible accounts of cognition and cognitive development.

## 1 Introduction

With the improving performance of pre-trained language models (Touvron et al., 2023; Gemini Team, 2023; OpenAI, 2023; Wei et al., 2022), researchers are increasingly advocating for their use as computational models of cognition (Piantadosi, 2023; Mahowald et al., 2024; Warstadt and Bowman, 2024; Coda-Forno et al., 2024). This is true for many domains including mathematical reasoning (Shah et al., 2023; Ahn et al., 2024), language comprehension (Warstadt et al., 2020; Li et al., 2024; Hu et al., 2024a), concept understanding (Vemuri et al., 2024), spatial reasoning (Ramakrishnan et al., 2024) and analogical reasoning (Webb et al., 2023; Hu et al., 2023). For example, Shah et al. (2023) investigated the latent number representations of PLMs, finding that they showed the *distance*, *size*,

and *ratio* effects observed in humans and understood to be the behavioral signatures of a “mental number line” (Moyer and Landauer, 1967; Parkman, 1971; Halberda et al., 2008). To take another example, Raven’s Progressive Matrices test is the standard psychometric measure of *fluid reasoning*. Although Raven’s problems are visual, Webb et al. (2023) translated them to equivalent “digit encodings” and showed that PLMs perform as well as humans on this test. More generally, many works combine tests across multiple task domains to form comprehensive benchmarks that enable scientific evaluation of the alignment of ML models to human cognition (Chang et al., 2024; Zhuang et al., 2023; Shah et al., 2024; Coda-Forno et al., 2024; Wang et al., 2024; Tan et al., 2024).

Recently, researchers have begun using PLMs to additionally model the development of cognition in children (Hosseini et al., 2022; Kosoy et al., 2023; Frank, 2023; Shah et al., 2024; Tan et al., 2024). For example, Portelance et al. (2023) suggest the use of language models to predict the age of acquisition of words in children. Wang et al. (2024) use Piaget’s Theory of Cognitive Development to estimate that models like GPT-4o show cognitive abilities similar to 20-year-old humans. Instead of just looking at model end states, Shah et al. (2024) investigated developmental trajectories and path dependence: whether the performance improvements of PLMs over training track the growth of cognitive abilities in children over development. Similarly, Tan et al. (2024) explored developmental parallels by comparing the learning trajectories of vision-language models to both child and adult behavioral data. To take a final example, researchers have begun varying the exposure of PLMs to multiple languages during pre-training to understand the differential rates of bilingual language development (Evanson et al., 2023; Marian, 2023; Sharma et al., 2024).

## Our Contributions

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|--|--|
|  <b>Developmental Alignment</b>                             | We highlight the alignment of PLMs with human cognitive development and discuss how model checkpoints and training trajectories can mimic children’s developmental trajectories.   |
|  <b>Pitfalls of Commission and Omission</b>                 | We introduce a new categorization of pitfalls into those of <i>commission</i> (methodological mistakes, such as distal linking hypotheses) and those of <i>omission</i> (neglecting broader contexts like psychometric and developmental data), providing a newer framework for identifying error types. |
|  <b>Linking Hypotheses and Measures</b>                     | We provide a detailed critique of linking hypotheses, focusing on the need for a robust mapping between model outputs and human cognitive measures, and we warn about distal links that can obscure interpretability and scientific validity.  |
|  <b>Promises of Adjacent Fields</b>                         | We draw interdisciplinary parallels, such as comparing functional mapping in neuroscience to mechanistic interpretability in PLMs, and discuss how these analogies can generate hypotheses about neural activity.  |
|  <b>Best Practices for Credibility in Cognitive Science</b> | We enumerate explicit criteria for using PLMs as credible theories in cognitive science, such as focusing on functional alignment over explanatory adequacy and ensuring sufficiency in mapping between PLMs and human behavior.   |

Table 1: Summary of our contributions - distinctions between our work and previous work by [Ivanova \(2023\)](#) and [Mahowald et al. \(2024\)](#).

### Reader’s Guide to the paper

In this paper, we describe the pitfalls and promise of using PLMs and candidate theories in cognitive and developmental science. The contributions of this paper are threefold. (1) We first review the *pitfalls* of using PLMs in psychological science and caution researchers against over-interpreting the alignment of PLMs to human cognition and its trajectory over development. (2) Next, we review the *standard assumptions* researchers use to map measures of PLM performance to human performance measures. (3) Finally, we build upon previous work ([Ivanova, 2023](#); [Mahowald et al., 2024](#); [Cuskley et al., 2024](#); [Birhane and McGann, 2024](#)) in enumerating best practices for cognitive evaluations of PLMs (refer to table 1).

## 2 PLMs as theories in cognitive and developmental science

PLMs make promising candidates as theories of cognitive science due to the nature of language model training ([Hardy et al., 2023](#)). PLMs acquire a wide range of capabilities in the pre-training phase, essentially obtaining human-like behaviors “for free” without the need for extensive task-specific tuning or adaptations ([Demszky et al., 2023](#); [Weng, 2024](#); [Yang et al., 2024](#); [Minaee et al., 2024](#); [OpenAI, 2023](#)). For example, the probabilis-

tic nature of PLM text generation lures researchers to draw parallels with the human decision-making process, where humans anticipate future courses of action based on their past experiences and context. These models can provide insights into how humans may handle ambiguous situations where multiple interpretations are possible ([McGrath et al., 2020](#); [Gawlikowski et al., 2023](#); [Dong et al., 2024](#); [Belem et al., 2024](#)). Moving from cognitive science to developmental science, PLMs have been shown to gradually learn linguistic sensitivities to syntax, semantics, morphology, etc., from mere exposure to (i.e., masked word prediction of) large amounts of text data. This raises the possibility that their learning trajectories mimic the development trajectories of children acquiring language ([Aher et al., 2023](#); [Duan et al., 2024](#); [Shah et al., 2024](#)).

This allure of PLMs as theories of cognitive science also extends to adjacent research areas. One example is the ability to simulate personas using PLMs, which enables the proxying of human subjects ([Park et al., 2022](#); [Samuel et al., 2024](#); [Schuller et al., 2024](#); [Tseng et al., 2024](#)). This is especially important when real-world experiments with human participants are complex, resource intensive, and/or pose ethical challenges ([Aher et al., 2023](#); [Dillion et al., 2023](#); [Hämäläinen et al., 2023](#)). Another adjacent area is neuroscience: Functional

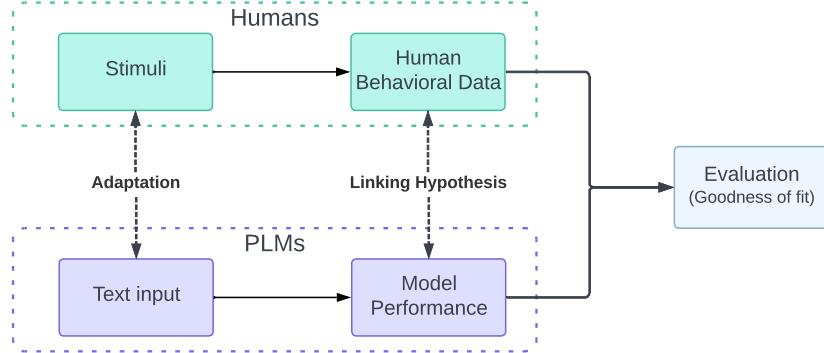


Figure 1: The three-stage mapping between human data and model performance when establishing the sufficiency and utility of PLMs as cognitive and developmental science models.

mapping in the neuroscience literature (i.e., mapping cognitive functions to their neural correlates) is similar to mechanistic interpretability in PLMs: both map functionalities to structure, provide a component-level analysis, and explain network interactions. This raises the question of whether the functional units of a PLM can be mapped to the functional units of the brain; this would enable their use in generating hypotheses about neural activity (Bzdok et al., 2024).

In its essence, we present an argument for the sufficiency and the utility of PLMs as cognitive and developmental science models: as long as *their performance profiles match those of humans*, then PLMs can be used to *predict* human behavior to specific stimuli. That is, we argue that matching the functional forms of the two is key, and that prediction is the more important criterion than explanation when applying ML models to cognitive phenomena (Breiman, 2003; Yarkoni and Westfall, 2017). Prior research in many domains has adopted this sufficiency argument (Niu et al., 2024; Ong, 2024).

In human studies, experiments are carefully designed to build and test hypotheses on the effect of cognitive phenomena. Independent of the phenomena under consideration, there are broadly three stages when mapping between the human data and model performance:

1. Adaptation of the experimental stimuli and task: The stimuli presented to humans and the task they are asked to perform are modified to match the input modality of PLMs.
2. Linking Hypothesis: The model outputs are mapped to indices of human performance.

3. Comparison to human performance: Model performance is compared against human performance to evaluate human alignment. This usually involves computing a measure of the *goodness of fit*.

These three stages are depicted in Figure 1). They provide a structure for evaluating the sufficiency or utility of PLMs as cognitive or developmental science theories.

#### Sufficiency criterion

*Under reasonable assumptions* about the three stages – (1) the adaptation of human stimuli to model inputs, (2) linking hypothesis for the model outputs, and (2) the comparison of model and human performance – *we are justified in using PLMs to predict human behavior*.

This sufficiency criterion extends into two key ideas that offer significant utility. The first is *generalizability and transferability*, as discussed by Binz et al. (2024), demonstrating predictive utility across  $n$  tasks builds confidence in the model’s performance on the  $n + 1$ th task. The second idea is *discovery*, which parallels drug discovery research, as highlighted by Vattikuti (2024). Here, achieving predictive utility across  $n$  tasks enables the generation of confident and novel candidate theories for human cognition based on the model’s behavior with novel stimuli.

### 3 Pitfalls of using PLMs as scientific theories

Although they show great promise, the assumptions made in the three-stage mapping process can lead to potential pitfalls when using PLMs for cognitive

modeling. We draw on current research to enumerate these pitfalls. Many have been noted before in the literature; a new conceptual contribution is to partition them into two distinct classes, pitfalls of commission and pitfalls of omission. Pitfalls of the commission are the methodological and meta-theoretical mistakes researchers may make when comparing PLMs and humans: using relatively distal linking hypotheses, insufficient consideration of the psychological plausibility of training corpora, etc. Pitfalls of omission stem from incorrectly assuming that cognitive ability (e.g., analogical reasoning) is a “module” and failing to consider the high-level context in which it functions: its relation to other cognitive abilities (psychometric data), its progression over-development (cognitive development data), and its neural correlates (neuroscience data).

**Pitfalls of Commission** The first pitfall of commission arises because researchers must use *linking hypotheses* to map model performance characteristics to human performance characteristics (Hale, 2001; Levy, 2008). For example, when modeling incremental sentence processing, the log probability of the next word (given the words that come before) according to a PLM can be mapped to the time humans take to read that word (Li et al., 2024). The problem is that these links are often quite distal, i.e., there is a large difference between the performance measures extracted from PLMs and those captured from humans, leaving it unclear whether PLMs are actually “explaining” cognitive science data. (See the next section for further discussion.)

Second, PLMs are opaque and have limited interpretability. When models and humans fail to align in their performance, the reason(s) why can be difficult to debug. This lack of interpretability is a barrier to treating these models as scientific theories (Kar et al., 2022; McGrath et al., 2023). Furthermore, commercial models often have many tuning interventions like supervised fine-tuning, instruction tuning, and RLHF/ RLAIF. While research shows that instruction tuning can more closely align PLMs to human brain-imaging data (Aw et al., 2023), lack of transparency in the tuning methods used makes it difficult to understand *why* they work when they do indeed work. It is true that there exist techniques to look at the mechanistic workings of a model, for example, mechanistic interpretability. However, these are often insufficient for investigating LLM misalignment to human cognition due to

their focus on low-level mechanisms, which are the wrong level of analysis for capturing the emergent, contextual, and symbolic aspects of human thought.

Finally, PLMs are trained on aggregate human data (like Wikipedia), and thus, their behavior may not always reflect the broad range of different behaviors observed across individuals. Although some research has explored fingerprinting human personas with PLMs, i.e., using prompts to elicit individualistic human-like behaviors (Park et al., 2022; Aher et al., 2023; Potter et al., 2024), there are conflicting views on whether models can simulate these personas (Milička et al., 2024) or not (Salewski et al., 2024).

**Pitfalls of Omission** Moving to pitfalls of omission, the first is that human brains and PLMs are architecturally different. Referring to Marr (2010) on the three levels of analysis, the architectural difference lies primarily at the implementational level, where the human brain relies on biological neural networks composed of neurons and synapses, while PLMs operate using artificial neural networks implemented in silicon-based hardware. Recent research attempts to map different aspects of PLMs (layers, attention heads, etc.) to different brain regions, seeking correspondence between model performance and functional neuroimaging measures. However, this work is in its infancy, and its viability (which requires a correspondence between NLP software and neural hardware) remains an open question (Hosseini et al., 2022; Kauf et al., 2023).

Second, most studies evaluating the cognitive alignment of PLMs focus on a narrow range of cognitive abilities and overlook correlations with other abilities. This is in line with the *experimental* approach to human behavior – but at odds with the *differential* or *psychometric* approach, which has also proven to be important (Cronbach, 1957). While recent research is developing larger benchmarks and expanding the evaluation of PLMs to suites of tests (Coda-Forno et al., 2024; Chang et al., 2024), there has been almost no attention paid to the correlations between the various tests. By contrast, psychometric approaches to human intelligence put the focus on the correlations across tests of a broad range of cognitive abilities: mathematical, verbal, spatial, fluid, and so on (Snow et al., 1984; Schneider and McGrew, 2012). This differential view is also in contrast with unified theories of cognition, the precursors to Artificial General Intelligence, that

attempt to model all cognitive abilities within a single computational framework (Anderson, 2009; Varma, 2011).

**Challenges of Development** Finally, we consider the pitfalls that come with treating PLMs as developmental science theories, i.e., of the progressions in children’s thinking over time.

First, PLM checkpoints are snapshots or fingerprints of the data on which they are trained. Most research only looks at final model checkpoints and evaluates cognitive alignment to adult thinking. Equally important is the question of whether, as language models observe more and more data, their performance is aligned to that of older and older children (Warstadt and Bowman, 2024; Frank, 2023; Shah et al., 2024). Developmental alignment is frequently overlooked because of the general unavailability of intermediate training checkpoints or because of resource constraints. This limits our understanding of the developmental fidelity of model training. However, recent open-source language modeling efforts to make available these checkpoints represent a promising opportunity to study developmental progressions (Biderman et al., 2023; Liu et al., 2023; Groeneveld et al., 2024).

Second, there are large differences in the nature of the data observed by PLMs versus those experienced by humans. PLMs are trained on magnitudes more textual data than the number of words seen by children (Huebner et al., 2021; Hosseini et al., 2022; Warstadt et al., 2023; Bhardwaj et al., 2024). That said, children learn from input from multiple senses (Smith and Gasser, 2005), whereas models are not embodied in nature (Chemero, 2023; Cusky et al., 2024; Birhane and McGann, 2024). Here, the emergence of vision-language models offers the potential to bridge the gap between the disembodied nature of PLMs and the multisensory learning of humans. However, this approach still faces certain limitations. For example, research suggests that while models can process simple visual features like color and size, models struggle with complex spatial and numerical reasoning tasks when applied to novel contexts or objects (Yiu et al., 2024).

Finally, for studies that have evaluated the developmental alignment of PLMs, the developmental trajectories observed in models might be artifacts of the pre-training order (Shah et al., 2024). Studies are needed to analyze training corpora and assess the impact of training curriculum design. This in-

cludes examining the sequence and nature of data presented during pre-training to distinguish genuine developmental progressions from artifacts introduced by training strategies.

### Pitfalls

Using PLMs as cognitive models potentially brings pitfalls of commission and omission and requires attention to the challenges of development. This means that researchers should be cautious when assessing the suitability of these models as proxies for human cognition and its development.

## 4 Linking Hypotheses - Mapping Model Performance to Human Performance

The “outputs” of PLMs are often quite different from the behavioral measures that cognitive scientists collect in their experiments and evaluate their theories against. Researchers use various linking hypotheses to map PLM performance to human performance measures. These assumptions necessarily define – and potentially limit – the strength and validity of the alignment. It is important to critically evaluate these linking hypotheses because they structure how we interpret the models’ cognitive capabilities. Below, we review different approaches to mapping indices of model behavior to human performance.

**Similarity computations** Many cognitive tasks require people to judge the similarity of two items. Examples range from Shepard’s classic psychophysical studies of people’s similarity judgments of perceptual stimuli (e.g., circles of differing diameters) (Shepard and Podgorny, 1978) to Griffiths’ current Bayesian and neural network models of how people judge the similarity of an exemplar to a category prototype (L Griffiths et al., 2008).

Human similarity judgments can be directly modeled by computing the similarity between the corresponding representations in a PLM’s latent space. This can be via cosine similarity or other metrics (Turney and Littman, 2005). One example of similarity computations in cognitive tasks comes from modeling the typicality effect, which is the finding that people regard some members as “better” examples of a category than others (Rosch, 1975; Bhatia and Richie, 2022). The typicality of an exemplar is commonly defined as the proportion

of humans that produce it when asked to enumerate the exemplars of a category, with larger proportions indicating greater typicality. In language models, the typicality of an exemplar for a category can be estimated by encoding the exemplar name as a string, passing it through the language model, and obtaining the corresponding word embedding. Thereafter, the similarity between this exemplar vector and the category prototype (e.g., the embedding obtained by encoding the category label as a string and passing it through the model) is calculated, with a higher value indicating that the exemplar is more typical (Misra et al., 2021; Vemuri et al., 2024).

Other cognitive tasks require comparing or discriminating between two items. There, a common linking hypothesis is that the greater the similarity between the items in the model’s latent space, the longer the comparison/discrimination time. Coming back to the example of a latent mental number line, Shah et al. (2023) map the time it takes to compare which of two numbers is greater to the similarity of their PLM encodings. The linking hypothesis is that the greater the similarity of (i.e., the less discriminable) the two encodings, the longer the predicted time for humans to judge which one is greater. Under this mapping, PLMs show the ‘distance, size, and ratio effects observed in humans (Moyer and Landauer, 1967) and thought to be behavioral signatures of possessing a “mental number line”.

More broadly, research shows the neural plausibility of vector-based representations in capturing human conceptual properties, including compositionality, feature computation, relational reasoning, and symbolic processing (Piantadosi et al., 2024).

There are two common obstacles to using similarity as a linking hypothesis. The first is that doing so requires models that make available the latent representations for similarity computations. The second is that this method suffers from problems due to tokenization. Humans use different granular units (words or subwords) compared to PLMs, which use tokens. This introduces misalignment – the mapping is inconsistent as one unit of text for humans may be mapped to two units for PLMs. For example, the word “Nine” for humans is represented as *N*, #*ine* in some PLMs such as Pythia (Biderman et al., 2023).

**Surprisal values** One way of quantifying the uncertainty of model generations is in terms of the

summation of their surprisals, i.e., their negative log probabilities. A common linking hypothesis is that higher surprisal values correspond to longer human response times. For instance, studies of reading (Rambelli et al., 2024; Ivanova et al., 2024b) and categorization (Misra et al., 2021) have found evidence for this correspondence. Similarly, Shain (2024) use PLMs to demonstrate strong surprisal predictability estimates of human reading times. Research also shows that surprisal values provide a better match to human plausibility judgments than prompts (Ivanova et al., 2024a). Finally, relative surprisal has been used to distinguish grammatical and ungrammatical sentences (Warstadt et al., 2020). In this case, surprisal enables direct comparison of the right answer with all possible candidate answers in a deterministic manner because PLMs will generate sequential probabilities for all strings, whether they are grammatical or not.

A problem with surprisal-based approaches is that they show high context sensitivity, i.e., the alignment of PLMs to humans often depends on the framing and the structure of the original prompt. For example, in mathematical tasks, models tend to achieve better alignment with human reasoning when they are prompted to generate longer texts and step-by-step reasoning chains (Jiang et al., 2024). This sensitivity to prompt structure makes it challenging to operationalize variations in PLM outputs in a way that mirrors the natural variances observed in human responses to stimuli. In some cases, surprisal is a weak proxy for human behavior: Van Schijndel and Linzen (2021) find that estimates of the time cost of word predictability derived using surprisal methods underestimate the magnitude of human garden path effects during processing of temporarily ambiguous sentences. More generally, surprisal fails to explain syntactic disambiguation difficulty (Huang et al., 2024). These findings highlight some failure modes of surprisal as a linking hypothesis and reveal the need to establish the empirical plausibility – goodness of fit score – of each linking hypothesis on each task. Surprisal makes assumptions about the relevance of probability distribution shifts to human sentence parsing and the relevance of information-theoretic measures to human cognition, which may be wrong or non-neutral and might be partially due to how surprisal is framed.

**Prompting** PLM generation is probabilistic and thus, non-deterministic, i.e., the same model can

give different results across inference runs. In prompting, PLM can be instructed to follow the same exercise as a human multiple times to generate a probability distribution over the output space. The probability of the correct output is then mapped to model confidence. Thus, prompting is very “proximal”, enabling direct comparison of the generated behavior of PLMs with that of humans and reducing (or even eliminating) the need for relatively “distal” and indirect linking hypotheses (Patel and Pavlick, 2021; Webb et al., 2023; Zahraei and Emami, 2024). For example, to evaluate a model on the BLiMP benchmark (Warstadt et al., 2020), a PLM can be prompted with:

Prompt: Which statement is grammatically correct?  
Your response must be "1" or "2".

**1. Noah likes to swim.**      **2. Noah likes to.**

The PLM can directly generate “1” for the correct answer, and its probability of doing so across inference runs can be directly compared with the probability of humans making the correct choice. This is much closer to the task humans perform than the more typical method of comparing the relative surprisal of the two sentences.

Another benefit of prompting is that it allows for *variable output length*. Tasks that benefit from this flexibility, like commonsense reasoning, are more suited for prompting (Yasunaga et al., 2023). This flexibility allows us to directly ask the model about its current state. For example, to measure the incremental semantic understanding of temporarily ambiguous sentences, Li et al. (2024) present a dichotomous verification sentence to the model after each word. The shifting probabilities of the sentences consistent with different semantic interpretations directly evidence the model’s online handling of ambiguity and response to disambiguating information. PLM prompting enables direct probing, which is often not possible in humans with behavioral measures (i.e., it would be disruptive to ask a human reader after each word to verify sentences), or even with using neuroimaging measures, which suffer their limitations to “look under the hood”.

Another example is the SAT analogical reasoning tasks (Turney, 2013). These are of the form A:B::? For example, consider the following SAT analogical reasoning problem:

**Analogy:** Runner : Marathon :: ?

**Options:**

- Envoy : Embassy
- Oarsman : Regatta
- Martyr : Massacre
- Horse : Stable

Such multiple choice question-based choice tasks can be operationalized using similarity, surprisal, or prompt-based reasoning. In the prompting case, we can force the generations to adhere to the goal: *answer the correct analogy in this output format: {"A": "B": "C": "D"}.*

Although it is quite “natural”, there are several limitations to the prompting approach. First, similarly to the surprisal method, PLMs are *not robust to the prompt format*. Answering prompts requires PLMs to (1) understand the prompt and (2) know the answer. Often, small variations in the input prompts lead to large changes in human alignment (Guo et al., 2024), and sometimes maximum performance characteristics are obtained on gibberish prompts (Deng et al., 2022). Second, PLMs may output an answer beyond the given candidate options for the prompting approach. For example, the outputted answer to the grammaticality judgment prompt above could be “It would be irresponsible to imply that the grammatical structure of a sentence is inconsequential, as clear communication is fundamental for safety and understanding” – output of an existing PLM observed by Cai et al. (2024). No human would make this response. In the same vein of errors, when asked to follow complex human-like experimental procedures, prompting methods sometimes fail in maintaining output format consistency, making it hard to use this method. Third, research also points towards certain tasks where prompting lacks efficacy and argues against the exact metalinguistic prompting approach presented above (Hu et al., 2023; Hu and Frank, 2024).

Overall, we see that some linking hypotheses are better suited for certain tasks than others, and sometimes, specific linking hypotheses fail to show any human behavior profile. Furthermore, it is hard to find the direction of error when the linking hypothesis fails to show a human behavioral profile, i.e., it is challenging to understand misalignment - whether it is due to over-simplified or over-complicated assumptions.

### Linking Hypothesis

Our findings reveal the need to establish the strong empirical plausibility – goodness of fit score – for each linking hypothesis on each task.

## 5 Criteria for Evaluating and Developing PLMs as Scientific Models

PLMs are increasingly being evaluated as models of cognitive and developmental science phenomena. In light of the discussion above, the review of some of the popular assumptions (linking hypotheses), and the common pitfalls outlined, we propose two sets of criteria for using PLMs for this purpose. While some may seem obvious or trivial, we believe that it is important to explicitly document them, given the evolving complexity and scope of PLMs. Explicit criteria provide a basis for interpreting results meaningfully, identifying limitations, and ensuring methodological rigor in their application as cognitive models.

### 5.1 Appropriateness

The first set concerns the *appropriateness* of PLMs as scientific tools for modeling cognitive and developmental phenomena:

#### Design multiple experiments to test alignment to each cognitive or developmental phenomenon

PLMs may track human performance characteristics well under one linking hypothesis on one type of test. However, this alignment may just be an artifact, for example, of pre-training data contamination, i.e., the accidental inclusion of evaluation samples in the pre-training data. We recommend *empirical triangulation* – conducting more experiments evaluating the same cognitive/developmental phenomena – to establish stronger empirical plausibility.

**Use multiple methods to interpret PLM successes and failures** PLMs lack explainability and interpretability due to their large size (McGrath et al., 2023). Some methods for PLM interpretation are often better than others. For example, in the experiments conducted by Li et al. (2024), incrementally constructed parse trees provided a better account of PLM alignment than the information from attention weights. It is typically not clear in advance which evaluation metric will be most insightful for a given set of models and cognitive tasks, *necessitating a multi-pronged approach*.

**Test the path-dependency of PLMs for developmental alignment** The claim that the final model state of a PLM approximates adult performance leads to the question of the path by which it arrived there. Ideally, the model’s performance improvements over training should also track the pro-

gression of cognitive abilities over development (Elman, 1996; Bengio et al., 2009). This would support researchers exploring the scaling of training data and model size in their investigations of human development. Inspired by (Tan et al., 2024), we encourage research into building age-aligned developmental benchmarks by sampling data aligned with children’s learning trajectories.

**Control for tuning techniques** PLMs are often tuned on specific data and in different ways, such as Instruction Tuning, Reinforcement Learning from Human Feedback (RLHF), etc. The technique used is not incidental. Rather, it can influence model behavior, which is important if the model’s output centers around tuning goals rather than developing a representation of world knowledge. Empirical evidence suggests that tuning methods result in better aligning PLMs with human cognition (Aw et al., 2023). We suggest evaluating cognitive alignment across multiple PLMs tuned with different objectives (e.g., instruction-tuned vs. RLHF-tuned).

**Remember the linking hypothesis** Adapting human experimental materials to textual counterparts that match the required modalities for PLMs requires making certain assumptions (refer to different operationalizations in section 4). These assumptions are not neutral, but rather part of why models may or may not align with human performance. For this reason, they need to be well-documented and explored in their own right. Additionally, transparency in selecting such assumptions helps establish the credibility and replicability of findings.

**Establish task correlations** Inspired by Snow et al. (1984), who study the correlations in human performance across different psychometric tests of intelligence, we propose a similar cross-task PLM evaluation paradigm. The goal will be to evaluate whether the pattern of cross-task correlations observed in humans is also produced by PLMs.

**Embodiment and interactiveness** Many researchers have advocated for the addition of more modalities in the pre-training process, such as vision, touch, etc., to emulate the learning environment of the child (Cuskley et al., 2024). While purely theoretical and speculative, the increasing “embodiment” of pre-training and the addition of external interactions may yield more substantial human alignment.

## 5.2 Development of PLMs for Cognitive Modeling

The second set of criteria is for guiding the *development* of PLMs as credible accounts of cognition and its development. This is a more open-ended task, and the following can be considered as mere suggestions to researchers:

**Pre-training data may benefit from developmentally plausible corpora** PLMs should be evaluated at regular intervals of pre-training to assess their potential developmental alignment. This step is often overlooked in current studies of cognitive alignment. This includes training on a curriculum based on the known developmental trajectories of knowledge and skill acquisition (Bhardwaj et al., 2024; Warstadt and Bowman, 2024; Frank, 2023; Hu et al., 2024b). For example, corpora could be ordered or sampled based on the age-of-acquisition of the words their text contains (Huebner et al., 2021; Portelance et al., 2023). Informed pre-training will allow us to better understand the developmental alignment of models.

**PLMs can first be tuned on a small number of “core” cognitive tasks and then evaluated on a broader range of cognitive tasks** For example, typicality experiments (Vemuri et al., 2024; Misra et al., 2021) could be used to preference-tune PLMs using reinforcement learning techniques. This might result in better cognitive alignment to a large number of tasks that all rely on human-like semantic representations (Vázquez Martínez, 2021; Vázquez Martínez et al., 2023). This builds off the promise of *generalization and transferability* for model alignment, where alignment on  $n$  tasks leads to predictive utility and alignment on  $n + 1$ th task (Binz et al., 2024).

## 6 Conclusion

This paper advocates for the use of Pre-trained Language Models (PLMs) as theoretical tools for investigating human cognition and its development through the three-stage model shown in Figure 1. In this advocacy, we are not alone (McGrath et al., 2023; Frank, 2023; Warstadt and Bowman, 2024; Mahowald et al., 2024). However, at the same time, we caution researchers toward the informed use of PLMs when making theoretical claims in the cognitive and developmental sciences. We have highlighted common pitfalls in this enterprise, reviewed the different assumptions (i.e., linking hypotheses)

used by researchers to map PLM performance to human performance, and outlined criteria for evaluating and developing PLMs as credible models of cognition and cognitive development. These criteria are intended to guide researchers in designing robust experiments (particularly using the three-stage criteria as a framework for experiment design), interpreting PLM behaviors accurately, and increasing fidelity to human data. Given the constantly evolving nature of the field, we call for researchers to continuously refine and expand these guidelines to match new advancements in NLP and cognitive science.

## 7 Limitations

(1) The paper highlights common pitfalls, linking hypotheses, and evaluative criteria while using PLMs for cognitive modeling. These constitute a set of sound views to aid new researchers in the field. They do not exhaustively cover every pitfall, hypothesis, or criterion. (2) The suggestions in this work are good-to-have practices that support using PLMs for open cognitive and developmental science. No one-answer-fits-all approach is possible. NLP is a developing field, and we recommend articulating newer guidelines and practices as newer and ever-larger PLMs are trained and deployed. (3) Our work calls for language technologies for the psychological sciences and provides criteria for developing credible accounts of cognition and cognitive development. Despite providing general guidelines, our work is theoretical and does not conduct experiments or offer empirical evidence of performance comparisons or other quantitative measures. In section 5, we suggest criteria by building upon and refining prior works based on empirical observations from the field. (4) PLMs, as described in this paper, are artificially designed systems that hope to reveal mechanisms of naturally evolving ones. Thus, researchers should keep the final goal in mind and not mistake a technological tool for an absolute source of insight. (5) This paper focuses on using PLMs for behaviorally benchmarking cognitive profiles of neurotypical and developmentally typical individuals. PLMs should also be used for simulating the behaviors of impaired individuals to better support them. (6) We do not address broader ethical implications of modeling cognitive impairments, limited cultural generalizability of PLMs trained on Western-centric corpora, and other factors outside the scope of our arguments.

## 8 Ethical Considerations

There are no significant risks associated with conducting this research beyond those associated with working with PLMs. There may be risks in misinterpreting the criteria enlisted in this study. The suggestions in this study are one-way: we wish to find human performance characteristics and behaviors in PLMs to help model psychological sciences and, in the future, to aid people with cognitive impairments. We do not advocate for developing PLMs to replace humans or suggest ways to reach Artificial General Intelligence. PLMs are experimental technologies, and future work using these models should be conducted cautiously.

## References

- Gati V Aher, Rosa I Arriaga, and Adam Tauman Kalai. 2023. Using large language models to simulate multiple humans and replicate human subject studies. In *International Conference on Machine Learning*, pages 337–371. PMLR.
- Janice Ahn, Rishu Verma, Renze Lou, Di Liu, Rui Zhang, and Wenpeng Yin. 2024. Large language models for mathematical reasoning: Progresses and challenges. *arXiv preprint arXiv:2402.00157*.
- John R Anderson. 2009. *How can the human mind occur in the physical universe?* Oxford University Press.
- Khai Loong Aw, Syrielle Montariol, Badr AlKhamissi, Martin Schrimpf, and Antoine Bosselut. 2023. Instruction-tuning aligns llms to the human brain. In *First Conference on Language Modeling*.
- Catarina G Belem, Markelle Kelly, Mark Steyvers, Sameer Singh, and Padhraic Smyth. 2024. Perceptions of linguistic uncertainty by language models and humans. *arXiv preprint arXiv:2407.15814*.
- Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In *Proceedings of the 26th annual international conference on machine learning*, pages 41–48.
- Khushi Bhardwaj, Raj Sanjay Shah, and Sashank Varma. 2024. [Pre-training llms using human-like development data corpus](#). Preprint, arXiv:2311.04666.
- Sudeep Bhatia and Russell Richie. 2022. Transformer networks of human conceptual knowledge. *Psychological Review*.
- Stella Biderman, Hailey Schoelkopf, Quentin Gregory Anthony, Herbie Bradley, Kyle O’Brien, Eric Halahan, Mohammad Aflah Khan, Shivanshu Purohit, USVSN Sai Prashanth, Edward Raff, et al. 2023. Pythia: A suite for analyzing large language models across training and scaling. In *International Conference on Machine Learning*, pages 2397–2430. PMLR.
- Marcel Binz, Elif Akata, Matthias Bethge, Franziska Brändle, Fred Callaway, Julian Coda-Forno, Peter Dayan, Can Demircan, Maria K Eckstein, Noémi Éltető, et al. 2024. Centaur: a foundation model of human cognition. *arXiv preprint arXiv:2410.20268*.
- Abeba Birhane and Marek McGann. 2024. Large models of what? mistaking engineering achievements for human linguistic agency. *Language Sciences*, 106:101672.
- Leo Breiman. 2003. Statistical modeling: The two cultures. *Quality control and applied statistics*, 48(1):81–82.
- Danilo Bzdok, Andrew Thieme, Oleksiy Levkovskyy, Paul Wren, Thomas Ray, and Siva Reddy. 2024. Data science opportunities of large language models for neuroscience and biomedicine. *Neuron*, 112(5):698–717.
- Alice Cai, Ian Arawjo, and Elena L Glassman. 2024. Antagonistic ai. *arXiv preprint arXiv:2402.07350*.
- Chen-Chi Chang, Ching-Yuan Chen, Hung-Shin Lee, and Chih-Cheng Lee. 2024. Benchmarking cognitive domains for llms: Insights from taiwanese hakka culture. *arXiv preprint arXiv:2409.01556*.
- Anthony Chemero. 2023. Llms differ from human cognition because they are not embodied. *Nature Human Behaviour*, 7(11):1828–1829.
- Julian Coda-Forno, Marcel Binz, Jane X Wang, and Eric Schulz. 2024. Cogbench: a large language model walks into a psychology lab. *arXiv preprint arXiv:2402.18225*.
- Lee Joseph Cronbach. 1957. [The two disciplines of scientific psychology](#). *American Psychologist*, 12:671–684.
- Christine Cuskley, Rebecca Woods, and Molly Flaherty. 2024. The limitations of large language models for understanding human language and cognition. *Open Mind*, 8:1058–1083.
- Dorottya Demszky, Diyi Yang, David S Yeager, Christopher J Bryan, Margaret Clapper, Susannah Chandhok, Johannes C Eichstaedt, Cameron Hecht, Jeremy Jamieson, Meghann Johnson, et al. 2023. Using large language models in psychology. *Nature Reviews Psychology*, 2(11):688–701.
- Mingkai Deng, Jianyu Wang, Cheng-Ping Hsieh, Yihan Wang, Han Guo, Tianmin Shu, Meng Song, Eric P Xing, and Zhitong Hu. 2022. Rlprompt: Optimizing discrete text prompts with reinforcement learning. *arXiv preprint arXiv:2205.12548*.
- Danica Dillion, Niket Tandon, Yuling Gu, and Kurt Gray. 2023. Can ai language models replace human participants? *Trends in Cognitive Sciences*, 27(7):597–600.

- Yijiang River Dong, Tiancheng Hu, and Nigel Collier. 2024. Can llm be a personalized judge? *arXiv preprint arXiv:2406.11657*.
- Xufeng Duan, Bei Xiao, Xuemei Tang, and Zhen-guang G Cai. 2024. Hlb: Benchmarking llms' humanlikeness in language use. *arXiv preprint arXiv:2409.15890*.
- Jeffrey L Elman. 1996. *Rethinking innateness: A connectionist perspective on development*, volume 10. MIT press.
- Linnea Evanson, Yair Lakretz, and Jean-Rémi King. 2023. Language acquisition: do children and language models follow similar learning stages? *arXiv preprint arXiv:2306.03586*.
- Michael C Frank. 2023. Bridging the data gap between children and large language models. *Trends in Cognitive Sciences*.
- Jakob Gawlikowski, Cedrique Rovile Njieutcheu Tassi, Mohsin Ali, Jongseok Lee, Matthias Humt, Jianxiang Feng, Anna Kruspe, Rudolph Triebel, Peter Jung, Ribana Roscher, et al. 2023. A survey of uncertainty in deep neural networks. *Artificial Intelligence Review*, 56(Suppl 1):1513–1589.
- Gemini Team. 2023. **Gemini: A family of highly capable multimodal models**. Preprint, arXiv:2312.11805.
- Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, A. Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, Shane Arora, David Atkinson, Russell Author, Khyathi Raghavi Chandu, Arman Cohan, Jennifer Dumas, Yanai Elazar, Yuling Gu, Jack Hessel, Tushar Khot, William Merrill, Jacob Daniel Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Valentina Pyatkin, Abhilasha Ravichander, Dustin Schwenk, Saurabh Shah, Will Smith, Emma Strubell, Nishant Subramani, Mitchell Wortsman, Pradeep Dasigi, Nathan Lambert, Kyle Richardson, Luke Zettlemoyer, Jesse Dodge, Kyle Lo, Luca Soldaini, Noah A. Smith, and Hanna Hajishirzi. 2024. **Olmo: Accelerating the science of language models**. arXiv preprint.
- Grace Guo, Jenna Kang, Raj Sanjay Shah, Hanspeter Pfister, and Sashank Varma. 2024. Understanding graphical perception in data visualization through vision-language models. In *NeurIPS 2024 Workshop on Behavioral Machine Learning*.
- Justin Halberda, Michèle MM Mazzocco, and Lisa Feigenson. 2008. Individual differences in non-verbal number acuity correlate with maths achievement. *Nature*, 455(7213):665–668.
- John Hale. 2001. **A probabilistic Earley parser as a psycholinguistic model**. In *Second Meeting of the North American Chapter of the Association for Computational Linguistics*.
- Perttu Hämäläinen, Mikke Tavast, and Anton Kunnari. 2023. Evaluating large language models in generating synthetic hci research data: a case study. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pages 1–19.
- Mathew Hardy, Ilia Sucholutsky, Bill Thompson, and Tom Griffiths. 2023. Large language models meet cognitive science: Llms as tools, models, and participants. In *Proceedings of the annual meeting of the cognitive science society*, volume 45.
- Eghbal A Hosseini, Martin Schrimpf, Yian Zhang, Samuel Bowman, Noga Zaslavsky, and Evelina Fedorenko. 2022. Artificial neural network language models align neurally and behaviorally with humans even after a developmentally realistic amount of training. *BioRxiv*, pages 2022–10.
- Jennifer Hu and Michael C Frank. 2024. Auxiliary task demands mask the capabilities of smaller language models. *arXiv preprint arXiv:2404.02418*.
- Jennifer Hu, Kyle Mahowald, Gary Lupyan, Anna Ivanova, and Roger Levy. 2024a. Language models align with human judgments on key grammatical constructions. *Proceedings of the National Academy of Sciences*, 121(36):e2400917121.
- Michael Y Hu, Aaron Mueller, Candace Ross, Adina Williams, Tal Linzen, Chengxu Zhuang, Ryan Cotterell, Leshem Choshen, Alex Warstadt, and Ethan Gotlieb Wilcox. 2024b. Findings of the second babylm challenge: Sample-efficient pretraining on developmentally plausible corpora. *arXiv preprint arXiv:2412.05149*.
- Xiaoyang Hu, Shane Storks, Richard L Lewis, and Joyce Chai. 2023. In-context analogical reasoning with pre-trained language models. *arXiv preprint arXiv:2305.17626*.
- Kuan-Jung Huang, Suhas Arehalli, Mari Kugemoto, Christian Muxica, Grusha Prasad, Brian Dillon, and Tal Linzen. 2024. Large-scale benchmark yields no evidence that language model surprisal explains syntactic disambiguation difficulty. *Journal of Memory and Language*, 137:104510.
- Philip A. Huebner, Elior Sulem, Fisher Cynthia, and Dan Roth. 2021. **BabyBERTA: Learning more grammar with small-scale child-directed language**. In *Proceedings of the 25th Conference on Computational Natural Language Learning*, pages 624–646, Online. Association for Computational Linguistics.
- Anna A Ivanova. 2023. Running cognitive evaluations on large language models: The do's and the don'ts. *arXiv preprint arXiv:2312.01276*.
- Anna A Ivanova, Aalok Sathe, Benjamin Lipkin, Evelina Fedorenko, and Jacob Andreas. 2024a. Log probability scores provide a closer match to human plausibility judgments than prompt-based evaluations.

- Anna A Ivanova, Aalok Sathe, Benjamin Lipkin, Unnathi Kumar, Setayesh Radkani, Thomas H Clark, Carina Kauf, Jennifer Hu, RT Pramod, Gabriel Grand, et al. 2024b. Elements of world knowledge (ewok): A cognition-inspired framework for evaluating basic world knowledge in language models. *arXiv preprint arXiv:2405.09605*.
- Zhuoxuan Jiang, Haoyuan Peng, Shanshan Feng, Fan Li, and Dongsheng Li. 2024. Llms can find mathematical reasoning mistakes by pedagogical chain-of-thought. *arXiv preprint arXiv:2405.06705*.
- Kohitij Kar, Simon Kornblith, and Evelina Fedorenko. 2022. Interpretability of artificial neural network models in artificial intelligence versus neuroscience. *Nature Machine Intelligence*, 4(12):1065–1067.
- Carina Kauf, Anna A Ivanova, Giulia Rambelli, Emanuele Chersoni, Jingyuan Selena She, Zawad Chowdhury, Evelina Fedorenko, and Alessandro Lenci. 2023. Event knowledge in large language models: the gap between the impossible and the unlikely. *Cognitive Science*, 47(11):e13386.
- Eliza Kosoy, Emily Rose Reagan, Leslie Lai, Alison Gopnik, and Danielle Krettek Cobb. 2023. Comparing machines and children: Using developmental psychology experiments to assess the strengths and weaknesses of lambda responses. *arXiv preprint arXiv:2305.11243*.
- Thomas L Griffiths, Charles Kemp, and Joshua B Tenenbaum. 2008. Bayesian models of cognition.
- Roger Levy. 2008. *Expectation-based syntactic comprehension*. *Cognition*, 106(3):1126–1177.
- Andrew Li, Xianle Feng, Siddhant Narang, Austin Peng, Tianle Cai, Raj Sanjay Shah, and Sashank Varma. 2024. Incremental comprehension of garden-path sentences by large language models: Semantic interpretation, syntactic re-analysis, and attention.
- Zhengzhong Liu, Aurick Qiao, Willie Neiswanger, Hongyi Wang, Bowen Tan, Tianhua Tao, Junbo Li, Yuqi Wang, Suqi Sun, Omkar Pangarkar, et al. 2023. Llm360: Towards fully transparent open-source llms. *arXiv preprint arXiv:2312.06550*.
- Kyle Mahowald, Anna A Ivanova, Idan A Blank, Nancy Kanwisher, Joshua B Tenenbaum, and Evelina Fedorenko. 2024. Dissociating language and thought in large language models. *Trends in Cognitive Sciences*.
- Viorica Marian. 2023. Studying second language acquisition in the age of large language models: Unlocking the mysteries of language and learning, a commentary on “age effects in second language acquisition: Expanding the emergentist account” by catherine l. caldwell-harris and brian macwhinney. *Brain and language*, 246.
- David Marr. 2010. *Vision: A computational investigation into the human representation and processing of visual information*. MIT press.
- Sam Whitman McGrath, Jacob Russin, Ellie Pavlick, and Roman Feiman. 2023. How can deep neural networks inform theory in psychological science?
- Sean McGrath, Parth Mehta, Alexandra Zytek, Isaac Lage, and Himabindu Lakkaraju. 2020. When does uncertainty matter?: Understanding the impact of predictive uncertainty in ml assisted decision making. *arXiv preprint arXiv:2011.06167*.
- Jiří Milička, Anna Marklová, Klára VanSlambrouck, Eva Pospíšilová, Jana Šimsová, Samuel Harvan, and Ondřej Drobil. 2024. Large language models are able to downplay their cognitive abilities to fit the persona they simulate. *Plos one*, 19(3):e0298522.
- Shervin Minaee, Tomas Mikolov, Narjes Nikzad, Meysam Chenaghlu, Richard Socher, Xavier Amatriain, and Jianfeng Gao. 2024. Large language models: A survey. *arXiv preprint arXiv:2402.06196*.
- Kanishka Misra, Allyson Ettinger, and Julia Taylor Rayz. 2021. Do language models learn typicality judgments from text? *arXiv preprint arXiv:2105.02987*.
- Robert S. Moyer and Thomas K. Landauer. 1967. Time required for judgements of numerical inequality. *Nature*, 215(5109):1519–1520.
- Qian Niu, Junyu Liu, Ziqian Bi, Pohsun Feng, Benji Peng, and Keyu Chen. 2024. Large language models and cognitive science: A comprehensive review of similarities, differences, and challenges. *arXiv preprint arXiv:2409.02387*.
- Desmond C Ong. 2024. Gpt-ology, computational models, silicon sampling: How should we think about llms in cognitive science? *arXiv preprint arXiv:2406.09464*.
- OpenAI. 2023. *Gpt-4 technical report*. Preprint, arXiv:2303.08774.
- Joon Sung Park, Lindsay Popowski, Carrie Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2022. Social simulacra: Creating populated prototypes for social computing systems. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*, pages 1–18.
- John M Parkman. 1971. Temporal aspects of digit and letter inequality judgments. *Journal of experimental psychology*, 91(2):191.
- Roma Patel and Ellie Pavlick. 2021. Mapping language models to grounded conceptual spaces. In *International conference on learning representations*.
- Steven Piantadosi. 2023. Modern language models refute chomsky’s approach to language. *Lingbuzz Preprint*, lingbuzz, 7180.
- Steven T Piantadosi, Dyana CY Muller, Joshua S Rule, Karthikeya Kaushik, Mark Gorenstein, Elena R Leib, and Emily Sanford. 2024. Why concepts are (probably) vectors. *Trends in Cognitive Sciences*.

- Eva Portelance, Yuguang Duan, Michael C. Frank, and Gary Lupyan. 2023. Predicting age of acquisition for children’s early vocabulary in five languages using language model surprisal. *Cognitive science*, 47:9:e13334.
- Yujin Potter, Shiyang Lai, Junsol Kim, James Evans, and Dawn Song. 2024. Hidden persuaders: Llms’ political leaning and their influence on voters. *arXiv preprint arXiv:2410.24190*.
- Santhosh Kumar Ramakrishnan, Erik Wijmans, Philipp Kraehenbuehl, and Vladlen Koltun. 2024. Does spatial cognition emerge in frontier models? *arXiv preprint arXiv:2410.06468*.
- Giulia Rambelli, Emmanuele Chersoni, Davide Testa, Philippe Blache, and Alessandro Lenci. 2024. Neural generative models and the parallel architecture of language: A critical review and outlook. *Topics in cognitive science*.
- Eleanor Rosch. 1975. Cognitive representations of semantic categories. *Journal of Experimental Psychology: General*, 104(3):192.
- Leonard Salewski, Stephan Alaniz, Isabel Rio-Torto, Eric Schulz, and Zeynep Akata. 2024. In-context impersonation reveals large language models’ strengths and biases. *Advances in Neural Information Processing Systems*, 36.
- Vinay Samuel, Henry Peng Zou, Yue Zhou, Shreyas Chaudhari, Ashwin Kalyan, Tanmay Rajpurohit, Ameet Deshpande, Karthik Narasimhan, and Vishvak Murahari. 2024. Personagym: Evaluating persona agents and llms. *arXiv preprint arXiv:2407.18416*.
- W Joel Schneider and Kevin S McGrew. 2012. The cattell-horn-carroll model of intelligence.
- Andreas Schuller, Doris Janssen, Julian Blumenröther, Theresa Maria Probst, Michael Schmidt, and Chandan Kumar. 2024. Generating personas using llms and assessing their viability. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, pages 1–7.
- Raj Shah, Khushi Bhardwaj, and Sashank Varma. 2024. Development of cognitive intelligence in pre-trained language models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 9632–9657.
- Raj Sanjay Shah, Vijay Marupudi, Reba Koenen, Khushi Bhardwaj, and Sashank Varma. 2023. **Numeric magnitude comparison effects in large language models.** *Preprint*, arXiv:2305.10782.
- Cory Shain. 2024. Word frequency and predictability dissociate in naturalistic reading. *Open Mind*, 8:177–201.
- Mihir Sharma, Ryan Ding, Raj Sanjay Shah, and Sashank Varma. 2024. Monolingual and bilingual language acquisition in language models.
- Roger N Shepard and Peter Podgorny. 1978. Cognitive processes that resemble perceptual processes. In *Handbook of learning and cognitive processes: Vol. 5. Human information processing*, pages 189–237. Erlbaum Hillsdale, NJ.
- Linda Smith and Michael Gasser. 2005. The development of embodied cognition: Six lessons from babies. *Artificial life*, 11(1-2):13–29.
- Richard E Snow, Patrick C Kyllonen, Brachia Marschalek, et al. 1984. The topography of ability and learning correlations. *Advances in the psychology of human intelligence*, 2(S 47):103.
- Alvin Wei Ming Tan, Sunny Yu, Bria Long, Wan-jing Anya Ma, Tonya Murray, Rebecca D Silverman, Jason D Yeatman, and Michael C Frank. 2024. Devbench: A multimodal developmental benchmark for language learning. *arXiv preprint arXiv:2406.10215*.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. **Llama: Open and efficient foundation language models.** *Preprint*, arXiv:2302.13971.
- Yu-Min Tseng, Yu-Chao Huang, Teng-Yun Hsiao, Yu-Ching Hsu, Jia-Yin Foo, Chao-Wei Huang, and Yun-Nung Chen. 2024. Two tales of persona in llms: A survey of role-playing and personalization. *arXiv preprint arXiv:2406.01171*.
- Peter D. Turney. 2013. **Distributional semantics beyond words: Supervised learning of analogy and paraphrase.** *Transactions of the Association for Computational Linguistics*, 1:353–366.
- Peter D Turney and Michael L Littman. 2005. Corpus-based learning of analogies and semantic relations. *Machine Learning*, 60:251–278.
- Marten Van Schijndel and Tal Linzen. 2021. Single-stage prediction models do not explain the magnitude of syntactic disambiguation difficulty. *Cognitive science*, 45(6):e12988.
- Sashank Varma. 2011. Criteria for the design and evaluation of cognitive architectures. *Cognitive science*, 35(7):1329–1351.
- Manoj Chowdary Vattikuti. 2024. Improving drug discovery and development using ai: Opportunities and challenges. *Research-gate journal*, 10(10).
- Héctor Javier Vázquez Martínez. 2021. **The acceptability delta criterion: Testing knowledge of language using the gradience of sentence acceptability.** In *Proceedings of the Fourth BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*, pages 479–495, Punta Cana, Dominican Republic. Association for Computational Linguistics.

- Héctor Javier Vázquez Martínez, Annika Heuser, Charles Yang, and Jordan Kodner. 2023. Evaluating neural language models as cognitive models of language acquisition. In *Proceedings of the 1st Gen-Bench Workshop on (Benchmarking) Generalisation in NLP*, pages 48–64, Singapore. Association for Computational Linguistics.
- Siddhartha K Vemuri, Raj Sanjay Shah, and Sashank Varma. 2024. How well do deep learning models capture human concepts? the case of the typicality effect.
- Xinglin Wang, Peiwen Yuan, Shaoxiong Feng, Yiwei Li, Boyuan Pan, Heda Wang, Yao Hu, and Kan Li. 2024. Coglm: Tracking cognitive development of large language models. *arXiv preprint arXiv:2408.09150*.
- Alex Warstadt and Samuel R. Bowman. 2024. What artificial neural networks can tell us about human language acquisition. *Preprint*, arXiv:2208.07998.
- Alex Warstadt, Aaron Mueller, Leshem Choshen, Ethan Wilcox, Chengxu Zhuang, Juan Ciro, Rafael Mosquera, Bhargavi Paranjape, Adina Williams, Tal Linzen, and Ryan Cotterell, editors. 2023. *Proceedings of the BabyLM Challenge at the 27th Conference on Computational Natural Language Learning*. Association for Computational Linguistics, Singapore.
- Alex Warstadt, Alicia Parrish, Haokun Liu, Anhad Mohnaney, Wei Peng, Sheng-Fu Wang, and Samuel R Bowman. 2020. Blimp: The benchmark of linguistic minimal pairs for english. *Transactions of the Association for Computational Linguistics*, 8:377–392.
- Taylor Webb, Keith J Holyoak, and Hongjing Lu. 2023. Emergent analogical reasoning in large language models. *Nature Human Behaviour*, 7(9):1526–1541.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682*.
- Benjue Weng. 2024. Navigating the landscape of large language models: A comprehensive review and analysis of paradigms and fine-tuning strategies. *arXiv preprint arXiv:2404.09022*.
- Haoran Yang, Yumeng Zhang, Jiaqi Xu, Hongyuan Lu, Pheng Ann Heng, and Wai Lam. 2024. Unveiling the generalization power of fine-tuned large language models. *arXiv preprint arXiv:2403.09162*.
- Tal Yarkoni and Jacob Westfall. 2017. Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12:1100 – 1122.
- Michihiro Yasunaga, Xinyun Chen, Yujia Li, Panupong Pasupat, Jure Leskovec, Percy Liang, Ed H Chi, and Denny Zhou. 2023. Large language models as analogical reasoners. *arXiv preprint arXiv:2310.01714*.
- Eunice Yiu, Maan Qraitem, Charlie Wong, Anisa Noor Majhi, Yutong Bai, Shiry Ginosar, Alison Gopnik, and Kate Saenko. 2024. Kiva: Kid-inspired visual analogies for testing large multimodal models. *arXiv preprint arXiv:2407.17773*.
- Pardis Sadat Zahraei and Ali Emami. 2024. Wsc+: Enhancing the winograd schema challenge using tree-of-experts. *arXiv preprint arXiv:2401.17703*.
- Yan Zhuang, Qi Liu, Yuting Ning, Weizhe Huang, Rui Lv, Zhenya Huang, Guanhao Zhao, Zheng Zhang, Qingyang Mao, Shijin Wang, et al. 2023. Efficiently measuring the cognitive ability of llms: An adaptive testing perspective. *arXiv preprint arXiv:2306.10512*.