CAN LARGE LANGUAGE MODELS GENERALIZE ANALOGY SOLVING LIKE CHILDREN CAN?

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ABSTRACT

When we solve an analogy we transfer information from a known context to a new one through abstract rules and relational similarity. In people, the ability to solve analogies such as "body: feet :: table: ?" emerges in childhood, and appears to transfer easily to other domains, such as the visual domain "(:):: <:?". Recent research shows that large language models (LLMs) can solve various forms of analogies. However, can LLMs generalize analogy solving to new domains like people can? To investigate this, we had children, adults, and LLMs solve a series of letter-string analogies (e.g., a b: a c:: j k:?) in the Latin alphabet, in a near transfer domain (Greek alphabet), and a far transfer domain (list of symbols). As expected, children and adults easily generalized their knowledge to unfamiliar domains, whereas LLMs did not. This key difference between human and AI performance is evidence that these LLMs still struggle with robust human-like analogical transfer.

Keywords analogy · transfer · artificial intelligence · reasoning · cognitive development

Research Transparency Statement

General Disclosures

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Study One Disclosures

Preregistration: The hypotheses, methods and analysis plan were preregistered (https://osf.io/5u623) on July 26, 2023, after human data collection in June 2023, but prior to LLM data collection which began Oct 12, 2023 and prior to any data inspection or analysis. There were minor deviations from the preregistration (for details see Supplementary Table 1 A). Materials: All study materials are publicly available (https://osf.io/jdty3/). Data: All primary data are publicly available (https://osf.io/jdty3/). Analysis scripts: All analysis scripts are publicly available (https://osf.io/jdty3/).

1 Introduction

You may be familiar with the analogy "consciousness is like an iceberg". Here, people can intuitively infer the below-the-surface depth and complexity of consciousness by relating it to an iceberg, whose mass is mostly found under water, just as our subconscious dwells under our conscious minds. This intuitive ability emerges in childhood Goddu et al. (2020); Gentner (1988); Stevenson and Hickendorff (2018). However, it is a subject of debate whether analogical reasoning has emerged in Large Language Models (LLMs) Webb et al. (2023); Lewis and Mitchell (2024); Hodel and West (2023); Webb et al. (2024). More importantly, are LLMs able to solve analogies at this level of conceptual abstraction and generalize to novel domains Mitchell (2021); Shiffrin and Mitchell (2023)? In this study, we investigate analogical transfer at two levels of abstraction (near and far), and compare LLM performance not only to adults, but

also to children, who are still developing analogical reasoning abilities. We ask the question: Can LLMs can generalize analogy solving like children can?

Analogical reasoning, the process of applying a known concept to understand something new through relational similarity, is fundamental to the way people think and learn Holyoak (2012); Gentner and Hoyos (2017). This is because we humans can easily generalize – that is, transfer principles discovered in one domain to new domains that share varying degrees of similarity with the original (Doumas et al., 2022). This can be principles in near contexts that are similar in terms of concrete attributes (e.g., shape, "a pyramid is like an iceberg") or in farther contexts that are only similar in terms of abstract relations (e.g., abstraction of depth, "consciousness is like an iceberg") Barnett and Ceci (2002). Near analogies tend to be easier for both adults and children to solve than far analogies Stevenson et al. (2023); Jones et al. (2022); Thibaut and French (2016). And, in general, adults are better at solving analogies than children. But, when the required domain knowledge and a causal framing are present then children can solve analogies such as "body is to feet as table is to?" as early as the 3-4 years-old (e.g., Goddu et al., 2020; Goswami, 1991). And when analogies are presented in a more challenging or far context young children tend to revert to associative strategies, e.g., replying 'egg' to 'dog is to doghouse as chicken is to?' instead of 'chicken coop' Stevenson and Hickendorff (2018); Gentner (1988); Thibaut and French (2016).

There are many tasks used to study analogical reasoning and transfer in people, from verbal to geometric to scene analogy problems (e.g., Ichien et al., 2020; Richland et al., 2006; Mulholland et al., 1980). However, many of these tasks are either not suitable for children (e.g., verbal analogies may contain unfamiliar words or relations for children) or to LLMs (e.g., visual analogies designed for children are still difficult for today's multimodal models Yiu et al. (2024)). Therefore, we need a domain that is text-based, but doesn't require domain knowledge beyond what a typical child or LLM would know. Letter-string analogies fit the bill as they require very little domain knowledge and offer an idealized scenario to examine analogical reasoning in a "pure, uncontaminated way" (Hofstadter, 1984, p. 3). In these puzzles, a string of letters is transformed according to one or more rules, and the task is to use analogy and apply the same transformations to a new string. For example, "If abc changes to abd, what should pqr change to?" (Mitchell, 2021).

Letter-string analogy solving has been studied in human adults and LLMs. For example, (Webb et al., 2023) showed that GPT-3 is able to solve letter-string analogies better than college students. (Lewis and Mitchell, 2024) showed that GPT-models solved letter-string analogies at about 60% accuracy in the Latin alphabet domain, somewhat below the level of adults they tested. Interestingly, (Lewis and Mitchell, 2024) and (Hodel and West, 2023) found that GPT-3's performance degraded when presented with these same analogies using an alphabet of shuffled letters. Moreover, (Lewis and Mitchell, 2024) showed that GPT-models had great difficulty solving letter-string analogies in an unfamiliar alphabet of symbols, whereas people did not. As such, there is conflicting evidence of whether LLMs can generalize analogy solving to novel domains (Lewis and Mitchell, 2024; Webb et al., 2024; Hodel and West, 2023), something that comes easily to adults (e.g., Thibaut et al., 2022; Doumas et al., 2022), and that even children appear capable of when domains share structural similarities Chen (1996); Gentner and Toupin (1986); Bobrowicz et al. (2020); Holyoak et al. (1984). Thus, while there is some evidence to suggest that LLMs can solve letter-string analogies at around the same level as people, it is unclear whether these models understand the problem and are actually using analogical reasoning Opiełka et al. (2024); Stevenson et al. (2023); Moskvichev et al. (2023).

In this study, we investigate whether LLMs can generalize analogy solving to new domains like adults and 8-year-old children can at two levels of abstraction. To this end, we compare how adults, children, and LLMs generalize analogy solving on the letter-string task to both near (Greek alphabet) and far (Symbol list) domains.

2 Method

We compared 42 children (7-9 year-olds), 62 adults, and 54 runs of each of four LLMs (Anthropic's Claude-3.5, Google's Gemma-2 27B, Open AI's GPT-40, and Meta's Llama-3.1 405B) on a set of letter-string analogies under three alphabet conditions: Latin, Greek and a Symbol list.

2.1 Materials

2.1.1 Letter-String Analogy Task

Letter-string analogies, pioneered by Hofstadter 1984, are a type of analogy puzzle (A is to B as C is to D) involving alphabetic strings where one set of strings transforms to another, and the task is to use analogy to generalize the same transformation to a new string. For example, "If the string of letters **abc** changes to **abd**. How would you change the string **pqrs** in the 'same way'?" (Mitchell, 2021). Two things are happening here. First, the move from **abc** in term A to **abd** in term B shows that the last letter in the string, **c**, shifts to its successor in the alphabet, **d**. Second, the successor transformation must be generalized to the C term, a new string **pqrt**.

However, another possible (and more literal) solution to the problem could be **pqrd**. Here, we could apply a different rule, namely that the last letter is replaced with **d**. While letter-string analogies do not necessarily have a correct answer, there are answers that people tend to prefer, which is what we consider "correct" in this context. In this case, it would be **pqrt**.

All in all, there are several types of possible transformations from A to B and generalizations from A to C as described in (Webb et al., 2023). We use only the simplest transformations of successor, predecessor and repetition, and the generalizations are limited to shifting in the alphabet and letter repetitions, rules that children are expected to be familiar with.

The task items from the Latin alphabet are shown in Table 1.

Table 1. Letter-String Task, Latin Item Set

| item | $\mathbf{A} 	o \mathbf{B}$ | $\mathbf{C} \rightarrow ?$ | D | AB Rule | AC Rule |
|---------|-------------------------------|----------------------------|---------|---|---------------------------|
| Latin 1 | $a b \rightarrow a c$ | g h \rightarrow ? | g i | successor(last, 1) | shift |
| Latin 2 | $c \; d \to c \; c \; e \; e$ | $m n \rightarrow ?$ | m m o o | successor(last, 1), repetition(all, 2) | shift |
| Latin 3 | $e f \rightarrow e h$ | $k 1 \rightarrow ?$ | k n | successor(last, 2) | shift |
| Latin 4 | $d\:e\to d\:f\:f$ | g h \rightarrow ? | gii | successor(last, 1), repetition(last, 2) | shift |
| Latin 5 | $c \; d \to b \; d$ | $m m n n \rightarrow ?$ | 11 n n | predecessor(first, 1), repetition(all, 2) | shift, repetition(all, 2) |



Fig. 1.

Visual representation of letter-string analogy item 1. (a) Latin alphabet serves as the baseline domain, (b) Greek alphabet as the near transfer domain, and (c) abstract symbols as the far transfer domain. Each panel shows the same analogical problem structure using different alphabets to test transfer.

Alphabets For each of the items in the Latin alphabet we also created a near transfer version using the Greek alphabet and a far transfer version in our invented Symbol alphabet "*@ %! ^# ~ \$ { ? = :", see Figure 1. We chose the Greek alphabet as near transfer domain because Greek symbols are somewhat visually similar to the Latin alphabet, but otherwise unfamiliar to the children in our study. We presented actual Greek symbols to humans, but chose the written version (i.e., alpha, beta, etc.) for LLMs based on their ability to list the Greek alphabet in this form upon request. We chose to use an ordered list of Symbols for far transfer, because it is an unfamiliar 'alphabet' that neither people nor the LLMs had seen before in this context, but at the same time were both able to process (i.e., the children can identify differences visually and for the LLMs these are common symbol keys on a keyboard). The constructed items for each alphabet were kept consistent, where the same transformations and generalizations from item 1 of the Latin alphabet were also used for item 1 of the Greek and Symbol alphabets, see Table 1 in the Appendix for an overview of all items.

2.1.2 Human Data Collection

Procedure Both children and adults completed the task in an Internet browser. They were first shown the Latin alphabet and told that they would solve puzzles with these. For adults there was a simple example with feedback as the study was carried out fully online. For children, the interface was explained and demonstrated in person. Participants then solved two simple practice items without feedback (used to check understanding of task). Then for each alphabet, they were shown the list of letters/symbols and told they would again solve puzzles using these letters/symbols, where the Greek and Symbol alphabets were referred to as "secret code" letters. There were five items for each alphabet, with 15 items total. See Figure 2 for the instruction screens and Table 9 for an overview of all items.

Adults We collected adult data online from fluent English speakers through Prolific.com ¹. We recruited 68 adults of 18 years or older (M=24.0, SD =7.33, 50% female) who had an education level of completed secondary education or

¹https://www.prolific.com/







(a) Initial instructions

(b) Latin alphabet instructions

(c) Greek/Symbol instructions

Fig. 2.

Task instructions presented to adult participants. (a) General task introduction and practice instructions, (b) specific instructions for the Latin alphabet condition, and (c) modified instructions for Greek alphabet and Symbol conditions. These instruction screens were exclusive to adult participants and were not shown to children.

higher, and resided in the Netherlands or neighboring countries (as children were recruited in the Netherlands). We also required that they have no language disorders and have (corrected-to-) normal vision to ensure they could see/process the task, that they use a device at least 2x a week (to ensure digital fluency), and that they have a 95% or higher approval rating on Prolific to ensure high quality data from the participants. Based on the pre-registered exclusion criteria for adults (answering >80% of items), 6 adults were excluded.

Children Children's data was collected from 44 children (7-9 year-olds, M=8.26, SD=0.67) at local schools on an electronic tablet. The recruited schools were Montessori schools that emphasized natural materials and did not use tablets or computers at school. The researchers gave spoken instructions to the children given the limited reading abilities in this age group. The children were then allowed to complete the task independently. We excluded two of the 44 children, because they did not complete the task. We did not apply the pre-registered inclusion requirement of answering both practice items correctly, as the two children who made errors here accidentally submitted empty responses during practice without making this mistake during the test, and also met the other inclusion criteria.

2.1.3 LLM Data Collection

We collected data from LLMs from six types of models: Anthropic's Claude-3.5 and Claude-3; Google's Gemma-2-9B and Gemma-2 27B; Open AI's GPT-3, GPT-3.5, GPT-4, and GPT-40; Meta's Llama-3.1-8B, Llama-3.1-70B, Llama-3.1-405B; Mistral AI's Mixtral-8x7B and Mixtral-8x22B; Qwen's Qwen-1.5-72B and Qwen-1.5-110B.

In order to keep the conditions for the LLM data collection as similar to that of people and, especially to fairly compare LLM results to those of children, we presented all analogies in a zero-shot setting using the same instructions that we spoke to the children, with the exception of using "secret code letters" instead of Greek alphabet and list of symbols. The LLMs received the same two practice items without feedback that the children received.

Please note that the alphabet was specified before each item, just like in the human data collection. Also, following (Webb et al., 2023)'s approach to administering verbal analogies and digit matrices, all previous conversation with the LLM was pre-pended to each successive item so that the models could learn while testing just as people could. This seemed especially important because the exact same rules were applied in the same order from one alphabet set to the next. It is perhaps important to note that we also ran the tasks without pre-pending previous conversation, which resulted in lower LLM performance across the board (see Supplementary Material https://osf.io/jdty3/files/osfstorage).

We presented the analogies in chat completion mode using Python API's from Anthropic for Claude models, from Open AI for GPT models and from Together AI for the remaining models, which are all open-source. We specified a temperature of 0 for near-deterministic data collection and set the maximum number of tokens to 10.

For each model type, the newest and largest model had the best performance. Furthermore, the Mistral and Qwen models performed far worse than the other models. Therefore, to provide clear and concise results we report the results based on this selected set of models: Anthropic's Claude-3.5, Google's Gemma-2 27B, Open AI's GPT-40, and Meta's Llama-3.1 405B. The results of the other models can be found in the Supplementary Material https://osf.io/jdty3/files/osfstorage.

Item variants for LLMs In order to be able to make robust comparisons between individual LLMs and groups of people, we adopted a similar methodology to Webb et al. 2023 and administered approximately as many variants of the task to each LLM as we had people who solved it. To do so, we created variants of each item by systematically shifting all of the characters in the item. For example, "a b: a c:: l m:?" became "b c: b d:: m n:?" and repeated this to create the required 54 total parallel testlets (based on power analysis for our pre-registration). This allowed us to have robust estimates of LLM performance, while creating some variation in the data and enabling us to compute SE's for statistical analyses. Item difficulties for LLMs were expected to be very similar, but not exactly the same because LLM

problem solving is sensitive to how often tokens occur in pre-training data (Razeghi et al., 2022), as can also be seen in the results by Webb et al. 2023.

Prompting templates We administered each item using 5 different prompt templates, as prompt engineering can change the LLMs' performance on the task. Examples of the templates and results can be found in Appendix 10. The template If a b c changes to a b d, what does i j k change to? worked best on the whole and was therefore chosen for LLM data collection.

Procedure The LLM general instruction was as follows:

```
We are going to do puzzles with the letters or symbols 'a b c d e f g h i j k l m n o p q r s t u v w x y z'. Example if a changes to b, then j changes to k
```

This included a complete example that was not included in the human data collection.

The LLM item instruction was:

```
The {letter|symbol} list is '{Latin alphabet|Greek alphabet|Symbol list}'.
If {A} changes to {B}, what does {C} change to ?
```

The system instruction was:

```
You are a helpful assistant that solves letter-string analogies. Only give the answer, no other words or text.
```

3 Results

We use mixed ANOVAs to (1) compare performance between our between-subjects participant groups (Adults, Children, and each of the LLMs) on the Latin alphabet and (2) test whether each participant group could generalize analogy solving, perform similarly, across alphabets (i.e., our repeated within-subjects factor). Below we report the most important results. More detailed results, e.g. comparing all LLMs, can be found in our Supplementary Material (https://osf.io/jdty3/files/osfstorage).

3.1 RQ1: How well do LLMs solve letter-string analogy problems in the Latin alphabet compared to adults and children?

We expected LLMs to be able to solve letter-string analogies with the Latin alphabet at the same level as adults Webb et al. (2023) and that both adults and LLMs would outperform children Thibaut and French (2016) (hypotheses H1a-c). Similar to what we expected, adults and some LLMs, except Google's Gemma-2 27B and Anthropic's Claude 3.5, performed better than children in the Latin alphabet domain. Open AI's GPT-40 performed similarly to adults, followed closely by Meta's Llama-3.1 405B. See Figure 3 and Tables 2 and 3 for more detailed results.

Table 2.

Descriptive statistics on letter-string analogy performance by Participant Group and Alphabet

| Participant Group | n | Lat | in | Greek | | Symbol | |
|-------------------|----|------|------|-------|------|--------|------|
| | | Mean | SD | Mean | SD | Mean | SD |
| Adults | 62 | 0.88 | 0.16 | 0.91 | 0.13 | 0.89 | 0.23 |
| Children | 41 | 0.62 | 0.22 | 0.66 | 0.23 | 0.67 | 0.30 |
| Claude-3.5 | 54 | 0.68 | 0.18 | 0.62 | 0.21 | 0.46 | 0.24 |
| Gemma-2 27B | 54 | 0.60 | 0.24 | 0.39 | 0.20 | 0.14 | 0.15 |
| GPT-4o | 54 | 0.85 | 0.18 | 0.63 | 0.21 | 0.48 | 0.18 |
| Llama-3.1 405B | 54 | 0.79 | 0.16 | 0.74 | 0.19 | 0.27 | 0.20 |

Table 3.

Post hoc t-test results: Participant group comparisons on letter-string performance with children in Latin domain

| Alphabet | Group 1 | Group 2 | \mathbf{n}_1 | n_2 | t | p Adjusted |
|----------|----------|----------------|----------------|-------|-------|------------|
| Latin | Children | Adults | 42 | 62 | -6.57 | <.001 |
| Latin | Children | Claude-3.5 | 42 | 54 | -1.35 | 1.0 |
| Latin | Children | Gemma-2 27B | 42 | 54 | 0.471 | 1.0 |
| Latin | Children | GPT-4o | 42 | 54 | -5.41 | <.001 |
| Latin | Children | Llama-3.1 405B | 42 | 54 | -3.85 | =.001 |

3.2 RQ2: How well do adults, children and LLMs generalize letter-string analogy solving from the Latin (baseline) domain to the Greek (near) and Symbol (far) domains?

We expected adults and children to generalize analogy solving to other domains and therefore perform similarly across domains Doumas et al. (2022) (hypotheses H2a-b). The experiment was designed to test whether LLMs could also generalize to other domains. Given the mixed results in previous research we had no clear evidence to predict how LLMs would perform on the near (Greek) and far (Symbol) letter-string analogy domains, but we suspected that LLM performance would degrade in less familiar domains.

Indeed our results indicate that adults and children perform similarly across alphabets (see Figure 3). But, for the four LLMs we tested, Anthropic's Claude-3.5, Google's Gemma-2 27B, Open AI's GPT-40, and Meta's Llama-3.1 405B, performance indeed degraded in less familiar alphabets (ANOVA results shown in Table 4). More specifically, for each model, performance degraded significantly from the Latin to Greek alphabet (posthoc Bonferonni-corrected t-test results all p<.001, except for Llama-3.1 405Bp = 0.012) and then again from the Greek alphabet to the Symbol list (posthoc Bonferonni-corrected t-test results all p<.001).

Table 4.

Post hoc ANOVA Results for main Alphabet effect on letter-string performance by Participant Group

| Participant Group | Effect | DFn | DFd | \mathbf{F} | p Adjusted |
|-------------------|----------|------|-------|--------------|------------|
| Adults | alphabet | 1.59 | 96.9 | 0.95 | 1.000 |
| Children | alphabet | 2.00 | 76.0 | 0.27 | 1.000 |
| Claude-3.5 | alphabet | 1.65 | 87.6 | 29.5 | <.001 |
| Gemma-2 27B | alphabet | 2.00 | 106.0 | 88.2 | <.001 |
| GPT-4o | alphabet | 2.00 | 100.0 | 55.0 | <.001 |
| Llama-3.1 405B | alphabet | 1.70 | 90.1 | 135.0 | <.001 |

3.3 RQ3: Why can't LLMs generalize letter-string analogy solving like children?

3.4 Performance by Item

To understand why the LLM's had trouble generalizing letter-string analogy solving to the Greek and Symbol domains we first look at their performance per item as this may give insight into which rules were easier and more difficult for the LLMs to apply. Table 5 shows and overview. Here we see that the LLMs and humans perform best on item 1, that involves only the successor transformation, and worst on item 5, that involves both the predecessor transformation and repetition generalization. Because, item 2, also involves the same repetition rule as item 5, but was solved better by LLMs and children, it seems like the predecessor rule is what gives both LLMs and children the most trouble. The other item people and LLMs have relatively more trouble with is item 3. This item involves the second successor rule. In sum, the predecessor and second successor rules appear to be the most difficult rules from our item set for people and LLMs to apply.

3.5 Next-Previous Letter Task

To investigate this further, we designed the Next-Previous Letter Task to check that the LLMs had the requisite domain knowledge of predecessor, successor and second successor to perform our letter-string analogy task. The task involved providing an ordered list of letters/symbols and asking the LLMs what the previous and next letters were given a specific letter. We did this 5 times using an optimized prompt requesting to identify the letter: one before, two before (not in our

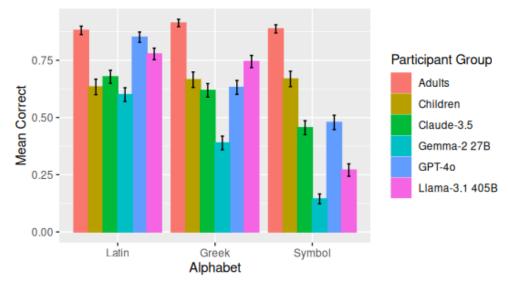


Fig. 3.

Performance comparison of human and LLM participants on letter-string analogies. Mean proportion correct scores are shown for each group across Latin (baseline), Greek (near transfer), and Symbol (far transfer) domains. Error bars represent standard error of the mean. Both adult and child participants maintained consistent performance across domains, while LLMs showed progressive performance degradation from baseline to far transfer conditions.

Table 5.

Mean proportion correct (SD) by Participant Group for each Item

| | | | Item | | |
|--------------------------|-------------|-------------|-------------|-------------|-------------|
| Participant Group | 1 | 2 | 3 | 4 | 5 |
| Adults | 0.97 (0.18) | 0.94 (0.25) | 0.82 (0.39) | 0.94 (0.24) | 0.81 (0.40) |
| Children | 0.85 (0.36) | 0.75 (0.44) | 0.52 (0.50) | 0.76(0.43) | 0.38(0.49) |
| Claude-3.5 | 0.90(0.30) | 0.65(0.48) | 0.54 (0.50) | 0.62(0.49) | 0.20(0.40) |
| Gemma-2 27B | 0.62 (0.49) | 0.27 (0.45) | 0.38 (0.49) | 0.37 (0.48) | 0.25 (0.43) |
| GPT-4o | 0.92 (0.27) | 0.73 (0.45) | 0.45 (0.50) | 0.78 (0.41) | 0.39 (0.49) |
| Llama-3.1 405B | 0.83 (0.37) | 0.62 (0.49) | 0.53 (0.50) | 0.57 (0.50) | 0.44 (0.50) |

item set), one after and two after, resulting in 20 items total. The exact prompts and items can be found in the Appendix D.

As can be seen in Figure 4, all models do best when asked to identify the next or previous letter and worse when it concerns identifying the second successor and second predecessor. Furthermore, Claude-3.5 performed well and similarly in all three domains, which is in contrast to its letter-string analogy performance that degrades from baseline to near to far domains. Similarly, GPT-40 performs well in the Latin and Greek domain, but in the letter-string task, its performance degrades from Latin to Greek. For Llama-3.1 405B transfer from the Latin to Greek to Symbol domain is similar across tasks, where in both tasks it does well with the Latin and Greek alphabets, but not the Symbol alphabet. Gemma-2 27B's performance is surprisingly more spotty here in the Greek domain than the Symbol domain. So, these results could explain why the LLMs have trouble with item 3, involving the second successor, but the results do not explain why they have trouble with item 5 involving the predecessor.

3.5.1 Rule Check Task

To better pinpoint why the LLMs had difficulty generalizing to the Greek and Symbol alphabet domains, we created a simplified item set that explicitly tested each rule used in the human item set in isolation. The rules were: (1) successor_1, the next letter; (2) successor_2, letter two places after; (3) predecessor_1, the previous letter; (4) predecessor_2, letter two places before; (5) repetition 1, repeating the last letter and (6) repetition 2, repeating both letters. Each rule was

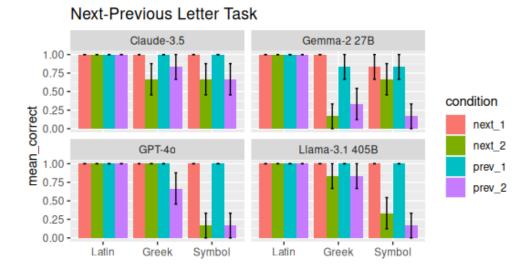


Fig. 4.

LLM performance by rule type across alphabet domains. All LLMs successfully apply rules in the Latin alphabet and maintain performance on repetition rules across domains. Performance degrades significantly for predecessor and second successor rules in the Symbol domain. Error bars represent standard error of the mean.

tested five times. Example items for the Latin alphabet are shown in Table 6. LLM system and instruction prompts were exactly the same as with the original items of our letter-string task.

Table 6.
Rule Check Task: Example Items From the Latin Alphabet.

| A | В | C | D | Rule AB |
|-----|---------|-----|------|---------------|
| c | d | h | i | successor_1 |
| c | e | h | j | successor_2 |
| d | c | h | g | predecessor_1 |
| e | c | h | f | predecessor_2 |
| c d | c d d | h i | hii | repetition_1 |
| c d | c c d d | h i | hhii | repetition_2 |

As can be see in Figure 5, the LLMs we tested can solve all rules in the Latin alphabet and have no problem with repetition rules in the Greek and Symbol domains. The successor and predecessor rules were solved to differing degrees in the Greek alphabet, with Claude-3.5 performing best followed by GPT-40. All models had trouble with the successor_2 and predecessor rules in the Symbol alphabet, where only the successor_1 rule sometimes formed an exception. This makes sense given the predict-the-next-token goal that LLMs are trained on McCoy et al. (2024).

3.5.2 Error Analysis

In general, when solving a letter-string analogies there are often multiple rules that could underlie the change from A to B Hofstadter and Mitchell (1994). In the very short strings that we use there is less ambiguity about the rule, than in longer strings. In our case, there are generally only two clearly correct responses. We considered the rules that people would generally prefer when responding, to be "correct", such as if **ab** changes to **ac**, then **gh** changes to **gi**. However, the literal rule of replacing the last letter with **c**, with response **gc** could also be considered correct.

Error Categories To examine errors in more detail we created a set of categories based on those from (Lewis and Mitchell, 2024) and extended these to account for common errors in children Stevenson and Hickendorff (2018). In the Literal rule category, the change from A to B is literally copied to C such as $\mathbf{a} \, \mathbf{b} : \mathbf{a} \, \mathbf{c} \, \mathbf{c} :: \mathbf{g} \, \mathbf{h} : \mathbf{g} \, \mathbf{c} \, \mathbf{c}$ rather than providing the more common response of $\mathbf{g} \, \mathbf{i} \, \mathbf{i}$. In the One rule category, the response is partially correct, but only (part of) one of the rules in the problem was applied, such as in responses to the previous example, $\mathbf{g} \, \mathbf{h} \, \mathbf{h}$ (only

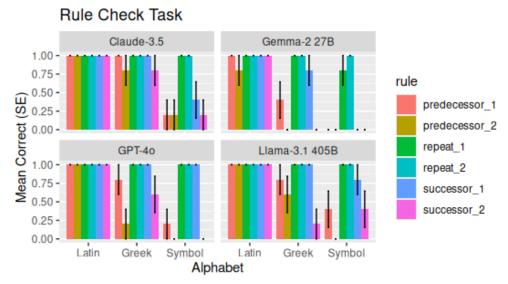


Fig. 5.

Rule-specific performance across alphabet domains for LLM participants. Mean accuracy scores are shown for each rule type (successor, predecessor, and repetition) across Latin (baseline), Greek (near transfer), and Symbol (far transfer) domains. Error bars represent standard error of the mean. LLMs maintain near perfect performance on all rules in Latin and on repetition rules across domains, but show significant degradation on predecessor and second successor rules in the Symbol domain.

repetition applied) or **g i** (only successor applied). Partially correct responses are common in children when problem load supersedes processing capacity Stevenson and Hickendorff (2018). In the **Incorrect rule** category, one of the other rules from our item set (i.e., successor, predecessor, repetition) was applied; for example, if the successor rule was used instead of the predecessor rule. For the **Copy rule**, the A, B or C term was copied as copying the C-term is common in young children (Stevenson and Hickendorff, 2018; Opiełka et al., 2024). Finally, all remaining erroneous responses were placed in the **Other rule** category. Given that our task was less complex than in (Lewis and Mitchell, 2024) (i.e., shorter strings, fewer rules), we were able to automatically code these categories.

Table 7.

Proportions of error categories by participant group

| Participant Group | Correct | Literal Rule | One Rule | Incorrect Rule | Copy Rule | Other Rule |
|-------------------|---------|--------------|----------|----------------|-----------|------------|
| Adults | 0.89 | 0.00 | 0.02 | 0.00 | 0.00 | 0.09 |
| Children | 0.66 | 0.00 | 0.06 | 0.01 | 0.00 | 0.23 |
| Claude-3.5 | 0.58 | 0.05 | 0.19 | 0.08 | 0.01 | 0.09 |
| Gemma-2 27B | 0.38 | 0.21 | 0.12 | 0.05 | 0.02 | 0.22 |
| GPT-4o | 0.65 | 0.13 | 0.07 | 0.02 | 0.00 | 0.12 |
| Llama-3.1 405B | 0.60 | 0.08 | 0.10 | 0.02 | 0.00 | 0.20 |

Note. 5% of children's responses were empty and are not included in the proportions shown.

What we see is that adults and children did not use the Literal rule, whereas all models used it sometimes, and for Gemma-2 27B and GPT-40 the Literal rule was one of the most common error types. The One rule was used most often in errors by Claude-3.5. The Incorrect and Copy rules were not used very often by people or models. And the Other rules were used most often by all, except Claude-3.5. Figure 6 shows a break down of Other rule use by Alphabet. Adults use an Other rule most often across the board, but they also have the fewest errors. Children's Other errors are also high across alphabets. Interestingly, GPT-40's Other responses are generally found in the Latin alphabet, while those for the other three LLMs are most prevalent in the Symbol alphabet.

String Distance between "Correct" and "Erroneous" Responses For each response we computed the Levenshtein string distance, also known as optimal string alignment distance, from the expected "correct" response to the given

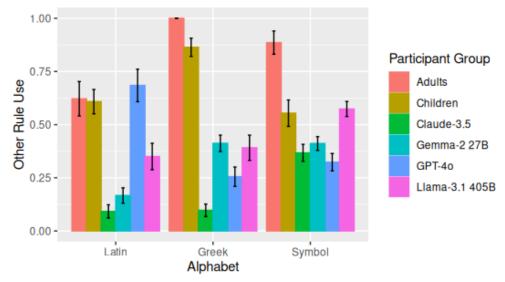


Fig. 6.

Analysis of erroneous responses by participant group and alphabet domain. Mean frequency of Other rule application is shown for children, adults, and LLMs across Latin, Greek, and Symbol alphabets. Error bars represent standard error of the mean.

response. This distance counts the minimum number of edit operations (insertion, deletion, substitution) needed to change one string into the other. Here we investigate whether there are differences in mean Levenshtein distance between adults, children and LLMs for "erroneous" responses. Figure 7 shows that that the Levenshtein distance for "erroneous" responses is greater for children on all alphabets than for LLMs. For adults, this is only the case for the Symbol alphabet. For, LLMs the Levenshtein distance hovers just under the 2 for all alphabets. Note also that the standard errors for LLMs are also much smaller, but this is because the adults and sometimes children (Greek, Symbol alphabets) had far fewer "erroneous" responses. These results tells us that when children provide "erroneous" answers their responses tended to differ largely from the expected response. For example, three children responded 'm m' to the item 'If c d changes to b d, what does m m n change to?', which has a Levenshtein distance of 6 from the expected response '11 n n'. The LLMs tended to provide 1 or 2 expected letters and 1 or 2 unexpected ones. For example, on the same item (and its variants) six GPT-40 runs provided '1 m m n' as a response, with a Levenshtein distance of 2 from the expected response.

4 Discussion

Our main finding is that the LLMs we tested, using similar prompts given to children, were not able to generalize letter-string analogy solving like children can. LLMs perform at or above the level of children on letter-string analogies in the familiar Latin alphabet, but their performance on these same problems reduces somewhat when using the Greek alphabet (near transfer) and deteriorates almost entirely when using our Symbol alphabet (far transfer).

Why can't LLMs generalize when solving letter-string analogies? For some models, this appears to be because they were unable to meet underlying requisites, such as indicating the predecessor or second successor. This would sense given the predict-the-next-token goal that LLMs are trained on McCoy et al. (2024). We tested this using the Next-Previous letter task, where models were given an ordered list of letters or symbols and asked to identify the (second) successor or predecessor to a given letter or symbol. These results could explain why the LLMs have trouble with the second successor, however the models had little trouble identifying the predecessor in this task. So, these results do not fully explain why LLM analogy solving performance degrades from the Latin to Greek to Symbol domains.

The problem with LLM's transfer from the Latin to other domains seems to lie in that the alphabet is too "unfamiliar". What we mean here is that the conceptual abstraction of what constitutes an alphabet, such as being an ordered sequence, does not appear to flexibly map to less familiar domains in LLMs like it does in people. Evidence for this comes from the Rule Check task, where we tested LLM performance on each of the rules separately. Here we see that the repetition rules could easily be applied to novel alphabets. This makes sense because if one were to create a function to repeat a letter in a string this could be done without knowing the alphabet or the order of the letters. In contrast, the models

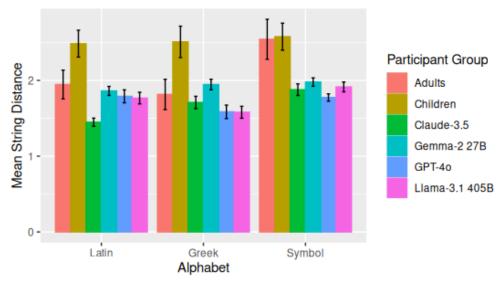


Fig. 7. String distance comparison of incorrect responses across participant groups and domains. Mean string distance between incorrect and expected responses is shown for children, adults, and LLMs across Latin, Greek, and Symbol alphabets. Error bars represent standard error of the mean. Children's erroneous responses tend to differ more from the expected response than those of LLMs for all alphabets. Adults erroneous responses only differ more for the Symbol alphabet.

had far more trouble with the predecessor and second successor rules, that, in order to solve correctly, both require that an alphabet is encoded as an ordered list of letters/symbols. This coincides with previous work, where Hodel and West (2023); Lewis and Mitchell (2024) found that GPT models were only able to solve letter-string analogies when presented with familiar letters in their standard order. As soon as unfamiliar symbols were used or familiar letters were shuffled, performance dropped drastically. We noted that in the Greek domain the letters were also ordered, but in our Symbol domain they were not, which could perhaps explain why Greek items were easier. So, to check whether order was also a factor in our Symbol domain, we adapted the task to make the Symbol alphabet ordered by their unicode values. However, this adaptation did not result in improved LLM performance.

We also investigated which kinds of errors people and LLMs made. This is important because letter-string analogies, like many four-term visual analogies apply ambiguous rules (e.g., Opiełka et al., 2024), and can be solved correctly in multiple ways Hofstadter and Mitchell (1994). The two main ways to solve the items in our task were what we considered the "correct" way (e.g., a b : a c c :: g h : g i i) and the "literal" way (e.g., a b : a c c :: g h : g c c). People did not use the "literal" rule, whereas the models all did to varying degrees (ranging from 5-21%). The other main difference between human and LLM errors, was that children's erroneous responses were generally more distant (measured with Levenshtein string distance) from the "correct" response than those of LLMs. This could be because children reverted to associative strategies that we didn't account for in our error coding scheme, given that this is the first time letter-string analogies have been administered to children. It will be interesting for future work to investigate children's development and 'shift' from associative to relational responses on letter-string analogies, especially compared to verbal and visual domains Stevenson and Hickendorff (2018); Gentner (1988).

Based on our results and previous work, these LLMs appear to have brittle, inflexible abstractions of what represents an alphabet in the context of the letter-string analogy task, despite being given the ordered list of letters/symbols before each item. It appears that LLMs like GPT-4 can only perform this abstraction by creating and executing code to map the novel alphabet to new positions Webb et al. (2024). This is of course very different from how children solve these problems.

In contrast, in children, familiarity with letters or symbols does not seem to influence how well they solve letter-string analogies. As such, our results add to the accumulating evidence that questions whether reasoning actually occurs in these LLMs (Wu et al., 2024; Gendron et al., 2024). Interestingly, in 1980, Schank concluded that there wasn't much intelligence in artificial intelligence given its limited ability to generalize. Similarly, Doumas et al. 2022 argue that robust analogical transfer is a uniquely human ability. Based on our findings so far we concur, and now ask the question: Is generalization to far domains indeed what separates human general intelligence from that of artificial

general intelligence? The challenge now is to create uncontaminated far generalization tasks that AI models have not been trained on to answer this question.

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A Supplemental Table: Deviations from Pre-registration

In this supplementary table 8 we specify the differences between our OSF preregistration and the methods and analyses carried out in this study.

Table 8.
Differences Between OSF Preregistration and Present Study

| | OSF Preregistration | Present Study |
|----------------------|---|--|
| Models in LLM Sample | GPT-3 (text-davinci-003) ChatGPT (GPT-4) | Claude-3.5 Gemma-2 27B GPT-40 Llama-3.1 405B |
| Scoring Method | Correct Partially correct Incorrect | Correct Incorrect |
| LLM Instruction | Instructions included in the prompt | General Instructions Item Instructions System Instructions |

B Complete Base Item Set

Table 9 shows the complete base item set administered to all three participant groups.

Table 9.

Complete Base Item Set Administered to Adults, Children, and LLMs

| Item ID | Alphabet | A | В | C | D | AB Rule | AC Rule |
|---------|----------|-----|---------|---------|---------|---|---------------------------|
| A | Practice | a | b | j | k | successor(all, 1) | shift |
| В | Practice | c d | c d d | j k | j k k | repetition(last, 2) | shift |
| 1 | Latin | a b | ас | g h | g i | successor(last, 1) | shift |
| 2 | Latin | c d | ссее | m n | m m o o | successor(last, 1), repetition(all, 2) | shift |
| 3 | Latin | e f | e h | k l | k n | successor(last, 2) | shift |
| 4 | Latin | d e | d f f | g h | gii | successor(last, 1), repetition(last, 2) | shift |
| 5 | Latin | c d | b d | m m n n | 11 n n | predecessor(first, 1) | shift, repetition(all, 2) |
| 1 | Greek | αβ | αγ | ζη | ζθ | successor(last, 1) | shift |
| 2 | Greek | γδ | γγεε | χλ | κκμμ | successor(last, 1) | shift |
| 3 | Greek | εζ | εϑ | ιx | ιμ | successor(last, 2) | shift |
| 4 | Greek | ηθ | ηιι | λμ | λνν | successor(last, 1), repetition(last, 2) | shift |
| 5 | Greek | βγ | άγ | ννξξ | μμξξ | predecessor(first, 1) | shift, repetition(all, 2) |
| 1 | Symbol | * @ | * % | ~ \$ | ~ { | successor(second, 1) | shift |
| 2 | Symbol | % ! | % % ^ ^ | =: | ==)) | successor(last, 1), repetition(all, 2) | shift |
| 3 | Symbol | @ % | @ ^ | # ~ | # { | successor(last, 2) | shift |
| 4 | Symbol | ! ^ | !## | \$ { | \$ = = | successor(last, 1), repetition(last, 2) | shift |
| 5 | Symbol | ^# | ! # | ==:: | { {:: | predecessor(first, 1) | shift, repetition(all, 2) |

C LLM prompt engineering results

We administered each letter-string analogy item to LLMs using 5 different prompt templates, as prompt engineering can change the LLMs' performance on the task. The templates were as follows.

- 1. If a b c changes to a b d, what does i j k change to?
- 2. a b c is to a b d, as i j k is to?
- 3. $a b c \rightarrow a b d \ n e f g \rightarrow ?$
- 4. Let's try to complete the pattern: $\n \ [a b c] [a b d] \ [i j k] [$
- 5. [a b c] [a b d] \n [i j k] [

As can be seen in Figure or Table 10, template 1, derived from Mitchell (2021) worked best overall. Template 4, the best template found by Webb et al. (2023) worked well in Latin and Greek alphabets, but not as well for the Symbol list, which makes sense because [and] are symbols themselves. Our results are based on template 1.

Table 10.

Prompt Template Performance Mean Correct (SE) for Selected Models

| Model | Template 1 | Template 2 | Template 3 | Template 4 | Template 5 |
|----------------|-------------|-------------|-------------|-------------|-------------|
| Claude-3.5 | 0.82 (0.10) | 0.88 (0.08) | 0.71 (0.11) | 0.53 (0.13) | 0.71 (0.11) |
| Gemma-2 27B | 0.59 (0.12) | 0.59 (0.12) | 0.41 (0.12) | 0.41 (0.12) | 0.29(0.11) |
| GPT-4o | 0.82 (0.10) | 0.71(0.11) | 0.71 (0.11) | 0.71 (0.11) | 0.71 (0.11) |
| Llama-3.1 405B | 0.71 (0.11) | 0.59 (0.12) | 0.59 (0.12) | 0.59 (0.12) | 0.35 (0.12) |
| Total | 0.74 (0.05) | 0.69 (0.06) | 0.60 (0.06) | 0.56 (0.06) | 0.52 (0.06) |

D Next-Previous Letter Task

The Next-Previous Letter Task was created to check whether LLMs were able to identify the previous and next two letters in an ordered sequence of letters. All items were administered one-by-one, without pre-pending previous conversation.

The LLM item instruction was:

Here is an ordered list of letters or symbols '{Latin alphabet|Greek alphabet|Symbol list}'.
Which letter or symbol is {one|two} {place|places} {before|after} {letter|symbol} ?
Respond with only the letter or symbol.

The system instruction was:

You are a helpful assistant that solves puzzles. Only give the answer, no other words or text.