Deep Neural Networks Evolve Human-like Attention Distribution
during Reading Comprehension

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Abstract

Attention is a key mechanism for information selection in both biological brains and many state-of-the-art deep neural networks (DNNs). Here, we investigate whether humans and DNNs allocate attention in comparable ways when reading a text passage to subsequently answer a specific question. We analyze 3 transformer-based DNNs that reach human-level performance when trained to perform the reading comprehension task. We find that the DNN attention distribution quantitatively resembles human attention distribution measured by fixation times. Human readers fixate longer on words that are more relevant to the question-answering task, demonstrating that attention is modulated by top-down reading goals, on top of lower-level visual and text features of the stimulus. Further analyses reveal that the attention weights in DNNs are also influenced by both top-down reading goals and lower-level stimulus features, with the shallow layers more strongly influenced by lower-level text features and the deep layers attending more to task-relevant words. Additionally, deep layers’ attention to task-relevant words gradually emerges when pre-trained DNN models are fine-tuned to perform the reading comprehension task, which coincides with the improvement in task performance. These results demonstrate that DNNs can evolve human-like attention distribution through task optimization, which suggests that human attention during goal-directed reading comprehension is a consequence of task optimization.
Introduction

Artificial intelligence and cognitive science separately investigate how machines and brains solve complex information processing problems, such as language comprehension and visual object recognition. As the artificial neural network approach in AI was in part originally inspired by biological neural networks, there is continuing interest in comparing the performance of artificial and biological neural networks\textsuperscript{1-7}. If human- or animal-like behaviors emerge in artificial neural networks, it indicates that the computations implemented in artificial neural networks can serve as a possible model for human/animal cognition\textsuperscript{8-10}. Indeed, it has been found that artificial neurons in modern DNNs can evolve receptive field properties that are comparable to those measured from animal visual cortices\textsuperscript{11}, and DNN models that have properties more consistent with biological neural systems tend to perform better at information processing tasks\textsuperscript{12,13}.

Traditional artificial neural networks mainly mimic lower-level or biophysical properties of neurons, while the new generation of DNN models also attempt to mimic high-level cognitive functions, e.g., attention. Attention mechanisms have greatly improved the performance of DNNs and have become a necessary component in state-of-the-art DNN models, especially in the field of natural language processing (NLP)\textsuperscript{14-18}. Recent studies have shown that the attention mechanism in DNN can play a wide variety of roles in language processing, e.g., to extract task relevant information\textsuperscript{19,20} and to analyze syntactic dependencies and semantic coreference\textsuperscript{21-23}. 
The attention mechanism in DNNs, however, is not designed to quantitatively simulate human attention, and few studies have systematically compared human and DNN attention during the same language processing task (see Bolotova et al. 2020\textsuperscript{24} for a notable exception). Therefore, it remains unclear to what extent the attention mechanisms in DNN language models are comparable to human attention and whether the attention mechanisms in DNN can serve as a model for human attention.

The human attention system has multiple components which contribute differently to different tasks. For example, when freely viewing an image, attention is primarily modulated by visual saliency, and this kind of attention is referred to as bottom-up attention\textsuperscript{25,26}. When searching for a target object in a visual scene, however, viewers attend more to possible locations of the target and objects with visual features more consistent with the target\textsuperscript{27}. This form of attention - induced by the task - is called top-down attention\textsuperscript{25,26}. In visual perception tasks that mainly engage bottom-up attention, a large number of studies have shown that neural networks can be trained to model human attention distribution measured through eye tracking\textsuperscript{28,29}. Recently, some models have also been proposed to model top-down attention\textsuperscript{7,30-33}. In the domain of language processing, computational models have been proposed to predict human readers’ fixations when they read simple sentences without a specific purpose\textsuperscript{34}, a task similar to free viewing. To our knowledge, however, no model has been proposed to predict human attention when readers read a passage with a specific goal, e.g., to answer a question.
Here we compare the attention distribution for humans and DNNs during a reading comprehension task in which humans or DNNs have to answer a question by reading a passage. We select this task since it is a benchmark task to test NLP algorithms and also a common task to test human verbal ability, e.g., in exams such as SAT, GRE, and TOEFL. This task is also suitable to investigate attention, since a passage contains an enormous amount of information, but only a small portion of it is typically relevant to answering a specific question, imposing a strong load for information selection. Finally, state-of-the-art DNN models have recently achieved human-level performance on the reading comprehension task for questions at the difficulty level corresponding to high school exams in China.

Using the reading comprehension task, we quantitatively analyze the attention mechanisms in the DNNs, characterized by the attention weight on each word, and also attention mechanisms in humans, measured by the fixation time. Note that both attention weights in DNNs and human eye fixations reflect intermediate processing steps instead of the outcome of reading comprehension. We aim to investigate three closely related questions. First, how is human and DNN attention modulated by stimulus features and the top-down reading goal, i.e., the need to answer a specific question? Second, do humans and DNNs show similar attention distributions? Third, how does the DNN attention distribution evolve during training and how does it relate to task performance?
Fig. 1 | Experimental procedure and DNN model. **a,** The experimental procedure in Study 1. In each trial, participants read a question first, and then read the corresponding passage, and finally proceed to read the question, coupled with 4 options, and answer it. **b,** The performance of humans and DNN models on the reading comprehension task. **c,** Architecture of the DNN models used for the reading comprehension task. The input to the models consists of all words in the passage and an integrated option, and also 3 special tokens, i.e., CLS, SEP₁, and SEP₂ (denoted as C, S₁, and S₂). The CLS token integrates information across words and is used to calculate a score that reflects how likely the option is the correct answer. The DNN model has 12 layers and has 12 attention heads in each layer. **d,** Illustration of the attention mechanism in a layer. In the models, each word/token is represented by a vector, and information is integrated across words(tokens only in the self-attention module. For example, the vectorial representation of the CLS token is a weighted sum of the vectorial representations of all words and tokens. The attention weight for each word in the passage, i.e., \( \alpha_{P_n} \), is the DNN attention analyzed in this study. Output of the self-attention model, i.e., \( C^{lh} \), is further processed by feedforward networks and other operations that do not engage information integration across words.
Examples of Human Attention and Prediction of Different Features

**Local question** ("At the top of the South Pole, your watch will ____.")

- **Fig. 2** | Examples of the human attention distribution and the human attention distribution predicted by different features. Panels a and b separately show the attention distribution for two passages and the corresponding questions are shown in the parenthesis. Human attention is quantified by the total fixation time per unit area. Textual features include word properties, e.g., word frequency and the position of a word in the passage. Layout features include visual features that can be processed without recognizing individual words. Task relevance contains human annotation about the contribution of each word to question answering. DNN attention includes all the layers and attention heads, and the DNN attention in the last layer is shown separately (averaged over attention heads).
Results

Human Attention Distribution and Influence Factors

In Study 1, the participants \( (N = 25 \) for each question) first read a question and then read a passage based on which the question should be answered. After reading the passage, the participants read 4 options related to the question and had to choose which option was the most suitable answer. Eight hundred question/passage pairs were presented, and the questions fell into two broad categories, i.e., local and global questions (see Methods for details). Local questions require attention to details while global questions concern the general understanding of a passage. The participants correctly answered 77.94\% questions on average (Fig. 1b, 77.49\% and 78.77\% for local and global questions, respectively).

While the participants read the passage, their eye gaze was monitored using an eye tracker, and their attention to each word was quantified by the total fixation time on the word. The results showed that longer words were fixated for longer time (Fig. S1), consistent with previous studies\textsuperscript{37}. Nevertheless, the fixation time on a word was expected to be positively related with the area the word occupied even when attention was uniformly distributed across the visual field. Therefore, here we further extracted the attention density by dividing the total fixation time on a word by the area the word occupied, and used this measure in subsequent analyses. The attention density clearly deviated from a uniform distribution (Fig. 2). To probe into the factors modulating human attention distribution, we quantified how the human attention distribution was influenced by multiple sets of features in the following.
Fig. 3 | Predicting human attention using different features. a,b. Panels a and b show the results of Study 1 and Study 2, respectively. The left plots show how well different sets of features can predict human attention density. In the middle and right plots, some features are regressed out from human attention, and the residual human attention is predicted by other features. Prediction accuracy that is significantly higher than chance is denoted by stars of the same color as the bar. c, The influence of word position on human attention. Humans generally attend more to the beginning of a passage, especially for global questions. d, The influence of task relevance on human attention. Humans allocate more attention to words that are more relevant to question answering. *P < 0.05; **P < 0.01; ***P < 0.001.
We first analyzed whether textual features, e.g., word length, word frequency, and a word’s position in a sentence, could predict human attention distribution using linear regression. The prediction accuracy, i.e., the correlation coefficient between the predicted and actual attention density, was significantly above chance (P = 0.002, permutation test, FDR corrected). Furthermore, the prediction accuracy was significantly higher for global questions than for local questions (P = 1.4 x 10^-4, bootstrap, FDR corrected) (Fig. 3a, the left plot). We then used the same regression analysis to analyze whether the visual layout of a passage could also influence attention distribution. Here, layout features referred to features induced by line changes (see Methods for details), which could be processed without word recognition. The prediction accuracy for layout features was also statistically significant (P = 0.002, permutation test, FDR corrected).

Textual features and layout features characterized properties of the stimulus that were invariant across tasks. In the following, we investigated whether the task, i.e., to answer a specific question, also modulated the attention distribution. To characterize the top-down influence of the task, we acquired annotations indicating each word’s contribution to question answering, i.e., task relevance (see Methods). As shown in the left plot of Fig. 3a, we found that task relevance could indeed significantly predict human attention distribution (P = 0.002, permutation test, FDR corrected). Since task relevance was not a well-established modulator of reading attention, we further analyzed whether the task relevance effect could be explained by the well-established
textual and layout effects. In this analysis, we first regressed out the influence of
textual and layout features from the human attention distribution, and found that the
residual attention distribution could still be predicted by task relevance ($P = 0.003$,
permutation test, FDR corrected) (Fig. 3a, middle plot). These results showed that the
top-down reading goal, quantified by task relevance, can modulate human attention,
on top of lower-level stimulus features, i.e., textual and layout features.

The linear regression analyses revealed that textual features, layout features, and task
relevance all modulated human attention. The prediction accuracy for different
features ranged between 0.2 and 0.6, comparable to the prediction accuracy of visual
saliency models when predicting human attention to images\textsuperscript{28,29}. Further analyses also
revealed how these features modulated human attention. For example, we found that
participants generally attended more to the beginning of a passage (Fig. 3c).
Furthermore, this effect was stronger for global questions, which potentially explained
why stimulus features could better predict the attention distribution for global
questions. Additionally, it was also found that participants attended more to words that
are more relevant to the question answering task (Fig. 3d).

**Attention Distributions in Humans and DNN**

We then investigated whether DNN models generated human-like attention
distribution. The general architecture of the models was illustrated in Fig. 1c. The
input to the models included all the words in the passage, integrated option, and 3
special tokens. One of the special token, i.e., CLS, was the decision variable, based on the final representation of which the DNN models decided whether an option was the correct answer or not. In the following, we analyzed the attention weight between the CLS token and each word in the passage (see Methods for details). In each layer of the DNN models, the vectorial representation of the CLS token was updated by a weighted sum of the vectorial representations of all input words and tokens. Therefore, the attention weight on a word could reflect how heavily the word contributed to the decision variable, i.e., the CLS token.

We analyzed 3 DNN models, i.e., BERT14, ALBERT16, and RoBERTa15, and the question answering performance of the 3 DNN models was within the range of human performance (Fig. 1b). Each of the 3 DNN models had 12 layers and each layer had 12 heads, each of which had a separate set of attention weights (Fig. 1cd). Consequently, each word had 144 attention weights (12 layers × 12 heads). In the following, we first tested whether the DNNs learned human-like attention distributions by attempting to decode human attention distribution from the 144 DNN attention weights using linear regression. Then, we analyzed whether the attention weights in different layers showed different properties.

Although the DNN models were only trained to perform the reading comprehension task and were blind to the human fixation data, it was found that the DNN attention weights could significantly predict human attention distribution (P = 0.002,
permutation test, FDR corrected), and the prediction accuracy was higher for global questions than for local questions ($P = 1.4 \times 10^{-4}$, bootstrap, FDR corrected) (Fig. 3a, left plot). The prediction accuracy of DNN attention weights was higher than that of textual features and task relevance. When compared with the predictions based on layout features, the predictions based on DNN attention weights were higher for local questions and lower for global questions. It should be mentioned, however, that layout features, which were induced by line changes, were not available in the input to DNN models.

DNN attention weights could model the human attention distribution, but did they capture information beyond the hand-crafted features, i.e., textual features, layout features, and task relevance features? We found that when the influences of textual and layout features were regressed out, the residual human attention distribution could still be explained by the DNN attention weights (Fig. 3a, the middle plot). This result suggested that the DNN attention weights contained information beyond basic stimulus features. Additionally, when the stimulus features and task relevance features were both regressed out, the residual human attention distribution remained significantly predicted by the DNN attention weights (Fig. 3a, the right plot). Therefore, DNN attention weights could model human attention and capture information beyond basic hand-crafted features.
Task Modulation in Humans
To further confirm that human attention received top-down modulation from the task, we conducted Study 2 as a control study. In Study 2, participants first read a passage without prior knowledge about the specific question to answer. After the first-pass passage reading, the participants read the question and were then allowed to read the passage again before answering the question. We analyzed the attention density during the first-pass reading of the passage, which is referred to as general-purpose reading.

For local questions, textual and layout features, but not task relevance, could predict human attention distribution during general-purpose reading ($P = 0.003, 0.003, \text{and} 1$ for textual features, layout features, and task relevance, permutation test, FDR corrected). For global questions, all three features could predict human attention distribution ($P = 0.003, 0.003, \text{and} 0.003$ for all 3 features, permutation test, FDR corrected). DNNs could also predict human attention distribution during general-purpose reading, but most of the effect was explained by textual and layout features (Fig. 3b, the middle plot).

Comparing the results obtained from Study 1 and Study 2, it was evident that human attention could be modulated by the specific reading goal, i.e., the question to answer, on top of textual and layout features. Goal-directed top-down attention, characterized in Study 1, could be modeled by either human-annotated task relevance or the DNN attention weights. In the absence of a specific reading goal, human attention in Study 2 was mainly influenced by stimulus features, e.g., textual and layout features, which were also captured by the DNN attention weights.
Fig. 4 | Influence of stimulus features and top-down task on each DNN layer. The same regression analyses in Fig. 3 are employed to analyze how the DNN attention is affected by lower-level stimulus features and top-down task relevance. Panels a and b show the results for the DNNs fine-tuned based on the reading comprehension task and the pre-trained DNNs that receive no fine-tuning. Each small dot shows the result from an attention head, and each large dot shows the average over heads of the same layer. Color indicates layer number. Shallow layers of both fine-tuned and pre-trained DNN are more sensitive to stimulus features. Deep layers of fine-tuned DNN, but not pre-trained DNN, are sensitive to task relevance.
DNN Attention in Different Layers

Previous studies have shown that different layers in DNN encoded different types of information\textsuperscript{38-40}. In the following, we analyzed whether the properties of DNN attention weights differed across layers. Since human attention was influenced by both bottom-up stimulus features and top-down task goal, in the following we also analyzed how these features influenced the attention weights in each DNN layer. Since the layout features were not available to the DNNs, we only considered textual features as stimulus features in this analysis. As shown in Fig. 4a, the attention weights in different layers were sensitive to different features. In general, shallow layers were more strongly influenced by textual features while deeper layers were more strongly influenced by the task relevance. This trend was observed in all 3 DNN models and was especially obvious for local questions. The transitional trajectory across layers, however, was model-dependent in the 2-dimensional feature space. In Fig. 2, examples were shown for the attention weights averaged over all 12 heads in the last layer of BERT, which resembled the human-annotated task relevance.

Evolution of DNN Attention during Fine-Tuning

All the 3 DNN models were pre-trained based on large-scale corpora and fine-tuned based on the reading comprehension task (see Methods for details). Was the DNN attention mechanism mainly shaped by the pre-training process or the fine-tuning process? We addressed this question by analyzing the attention weights in pre-trained DNN models that did not receive fine-tuning (Fig. 4b). It was found that the attention
weights of pre-trained DNN were sensitive to textual features in shallow layers but not sensitive to task relevance in deeper layers, suggesting that top-down attention in DNNs emerged during fine-tuning using the reading comprehension task.

We then analyzed how the attention weights of DNN changed during fine-tuning and whether such changes were related to the performance of question answering. We analyzed the properties of models that received different steps of fine-tuning. We found that the properties of shallow layers were barely influenced by fine-tuning (upper plots of Fig. 5ab and Fig. S2). Nevertheless, in deep layers, properties of the attention weights significantly changed during fine-tuning. In the last layer, for example, it was clear that the DNN attention weights became more sensitive to task relevance during fine-tuning, coinciding with the improvement in task performance (Fig. 5a, lower plots). Deep layer’s sensitivity to textual features, however, dropped during fine-tuning (Fig. 5b, lower plots). Therefore, fine-tuning directed deep layers’ attention towards task relevant information, sacrificing the sensitivity to textual features. Additionally, we found that the similarity between DNN attention weights and human attention was also boosted by fine-tuning (Fig. 6). This result further demonstrated that human-like attention in DNNs was the consequence of optimization of the reading comprehension task, instead of the consequence of more general pre-training language tasks.
Fig. 5 | Influence of fine-tuning on DNN attention and task performance. Each dot denotes a fine-tuning step (color coded). The fine-tuning process modulates the attention properties in the last but not first layer of DNN. For local questions, fine-tuning enhances the sensitivity to top-down task relevance while reducing the sensitivity to lower-level textual features, which correlates with the increase in task performance.
Fig. 6 | Influence of fine-tuning on the similarity between DNN and human attention. For local questions, fine-tuning clearly increases the similarity between DNN and human attention, coinciding with the increase in task performance. For global questions, the similarity between DNN and human attention is high even without fine-tuning and is not further boosted by fine-tuning.

Discussion

Since attention is a key mechanism for both the biological brain and artificial neural networks, it provides a common ground to quantitatively compare biological and artificial neural computations. Such comparisons, however, are challenging since biological and artificial neural networks are investigated in different fields using very different approaches. Typically, psychological/neuroscientific studies employ highly controlled experiments to test specific hypotheses about the biological brain, while artificial intelligence studies often focus on how to train computers to solve real world problems that are not necessarily optimized to test specific hypotheses. Therefore, it is challenging to directly compare data across the fields of psychology/neuroscience and artificial intelligence. The current study attempts to bridge this gap by acquiring a large
amount of high-quality psychological data, i.e., eye tracking data, using a real-world task that is of interest to the artificial intelligence community.

The current results show that DNNs can generate an attention distributions that resemble human attention, even when a given DNN is only optimized for the reading task. On the one hand, the results indicate that the attention mechanism in DNN could indeed be of biological relevance. On the other hand, it provides a potential computational explanation about why human readers allocate a different amount of attention across words when performing a real-world reading comprehension task: Human-like attention naturally emerges in a neural network as a consequence of task optimization\textsuperscript{12,13}. The current results are also consistent with the idea that attention in the biological brain can be interpreted a mechanism to optimally weight different cues for decision making\textsuperscript{41-43}.

A recent study compares human eye movements and attention weights in the last layer of BERT, when participants evaluate whether a passage is an appropriate answer to a question. It is demonstrated that the human fixation time is more similar to the attention weight in BERT than the simple term frequency–inverse document frequency (TF-IDF) weights\textsuperscript{24}. The current study significantly expands on this finding, investigating a more natural task based on a much larger dataset, and systematically compares how human and DNN attention in different layers are modulated by different stimulus features. The DNN attention mechanisms can take different forms and play different roles in different
tasks. Therefore, it remains unclear whether the conclusions in the current study can generalize to the attention mechanisms in other models. Nevertheless, the current study demonstrates that at least some DNN models have the capacity to evolve human-like attention, suggesting that human attention can be explained by task optimization. Furthermore, using the dataset and methods in the current study, future studies can easily quantify whether other models also evolve human-like attention distribution.

**Methods**

**Participants**

Study 1 enrolled 102 participants (19-30 years old, mean age, 22.9 years; 54 female), and each participant could participate in multiple experiments. Study 2 enrolled a separate group of 18 participants (21-26 years old, mean age, 23.4 years; 10 female). All participants were native Chinese speakers and were college students or graduate students at Zhejiang University, and were thus above the level required to answer high-school-level reading comprehension questions. English proficiency levels were further guaranteed by the following criterion for screening participants: a minimum score of 6 on IELTS, 80 on TOEFL, or 425 on CET6. The experimental procedures were approved by the Research Ethics Committee of the College of Medicine, Zhejiang University (2019–047). The participants provided written consent and were paid.

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1 The National College English Test (CET) is a national English test system developed to examine the English proficiency of undergraduate students in China. CET includes tests of two levels: a lower level test CET4 and a higher level test CET6.
Experimental materials

The reading materials were selected and adapted from the large-scale RACE dataset, a collection of reading comprehension questions in English exams for middle and high schools in China. We selected eight hundreds of high-school level questions from the test set of RACE and each question was associated with a distinct passage (117 to 456 words per passage). All questions were multiple-choice questions with 4 alternatives including only one correct option among them. The questions fell into 6 types, i.e., Cause ($N = 200$), Fact ($N = 200$), Inference ($N = 120$), Theme ($N = 100$), Title ($N = 100$), and Purpose ($N = 80$). The Cause, Fact, and Inference questions were concerned with the location, extraction, and comprehension of specific information from a passage, and were referred to as local questions. Questions of Theme, Title, and Purpose tested the understanding of a passage as a whole, and were referred to as global questions. We further acquired annotations about the relevance of each word to the question answering task. Details about the question types and the annotation procedures could be found in reference 44.

Experimental procedures

**Study 1:** Study 1 included all 800 passages, and different question types were separately tested in different experiments, hence six experiments in total. One participant could participate in multiple experiments, and each experiment included 25 participants. Before each experiment, participants were given a familiarization
session with 5 questions that were not used in the formal experiment. During the formal experiment, questions were presented in a randomized order. Considering the quantities of questions, for Cause and Fact questions, the experiment was carried out in 3 separate days (one third questions on each day), and for other question types the experiment was carried out in 2 days (fifty percent of questions on each day).

The experiment procedure in Study 1 was illustrated in Fig. 1a. In each trial, participants first read a question, pressed the space bar to read the corresponding passage, and then pressed it again to read the question coupled with 4 options and answer the question. The time limit for passage reading was 120 s. To encourage the participants to read as quickly as possible, the bonus they received for a specific question would decrease linearly over time. They did not receive any bonus for the question, however, if they gave a wrong answer. Furthermore, before answering the comprehension question, the participants reported whether they were confident that they could correctly answer the question. After answering the question, they also rated their confidence about their answer on the scale of 1-4 (low to high). The confidence ratings were not analyzed.

**Study 2:** Study 2 included 96 reading passages and questions, with 16 questions for each question type that were randomly selected from the questions used in Study 1. The study was carried out in 2 days, and none of the participants participated in Study 1. The familiarization procedure was identical to that in Study 1.
The procedure of Study 2 was similar to that of Study 1, and the main difference was that a 90-s first-pass passage reading stage was introduced at the beginning of each trial. During the first-pass passage reading, participants had no prior information of the relevant question. The participants could press the space bar to terminate the first-pass reading stage and to read a question. Then, participants read the passage for the second time with a time limit of 30 s, before proceeding to answer the question. In Study 2, the correctness of the answer was also the prerequisite for bonus, and the amount of bonus decreased linearly with the duration of second-pass passage reading.

**Stimulus presentation and eye tracking**

The text was presented using the bold Courier New font, and each letter occupied 14 × 27 pixels. We set the maximum number of letters on each line to 120 and used double space. We separated paragraphs by indenting the first line of each new paragraph. Participants sat about 880 mm from a monitor, at which each letter horizontally subtended approximately 0.25 degrees of visual angle.

Eye tracking data were recorded from the left eye with 500-Hz sampling rate (Eyelink Portable Duo, SR Research). The experiment stimuli were presented on a 24-inch monitor (1920x1080 resolution; 60 Hz refresh rate) and administered using MATLAB Psychtoolbox\textsuperscript{45}. Each experiment started with a 13-point calibration and validation of eye tracker, and the validation error was required to be below 0.5° of visual angle.
Furthermore, before each trial, a 1-point validation was applied, and if the calibration error was higher than 0.5°, a recalibration was carried out. Head movements were minimized using a chin and forehead rest.

**DNN models**

We tested 3 popular transformer-based DNN models, i.e., BERT\(^{14}\), ALBERT\(^{16}\), and RoBERTa\(^{15}\). ALBERT and RoBERTa were both adapted from BERT, and had the same basic structure. RoBERTa differed from BERT in its pre-training procedure\(^{15}\) while ALBERT applied factorized embedding parameterization and cross-layer parameter sharing to reduce memory consumption\(^{16}\). We fine-tuned DNN based on the training set of RACE. Following previous works\(^{15,16}\), each option was independently processed. For the \(i\)\(^{th}\) option (\(i = 1, 2, 3, \text{ or } 4\)), the question and the option were concatenated to form an integrated option. As shown in Fig. 1c, for the \(i\)\(^{th}\) option, the input to DNN was the following sequence:

\[
C_i, P_1, P_2, ..., P_N, S_{i,1}, O_{i,1}, O_{i,2}, ..., O_{i,M}, S_{i,2},
\]

where \(C_i, S_{i,1}, \text{ and } S_{i,2}\) denoted special tokens, i.e., the CLS, SEP\(_1\), and SEP\(_2\) tokens, separating different components of the input. \(P_1, P_2, ..., P_N\) denoted all the \(N\) words of a passage, while \(O_{i,1}, O_{i,2}, ..., O_{i,M}\) denoted all the \(M\) words of the \(i^{th}\) integrated option.

Each of the token was represented by a vector. The vectorial representation was updated in each layer, and in the following the output of the \(l^{th}\) layer was denoted as a superscript, e.g., \(C_i^l\). Following previous works\(^{15,16}\), we calculated a score for each option, which indicated the possibility that the option was the correct answer. The
score was calculated by first applying a linear transform to the final representation of the CLS token, i.e.,

\[ s_i = \Phi C_i^{12} \]

where \( C_i^{12} \) was the final output representation of CLS and \( \Phi \) was a vector learned from data. The score was independently calculated for each option and then normalized using the following equation:

\[ \text{score}_i = \frac{\exp(s_i)}{\sum_{i=1}^{4} \exp(s_i)}. \]

The answer to a question was determined as the option with highest score, and all the models were trained to maximize the logarithmic score of the correct option. All models were implemented based on HuggingFace and all hyperparameters for fine-tuning were adopted from previous studies (Table S1).

To isolate how the fine-tuning process modulated DNN attention, we also tested the pre-trained DNN which was not fine-tuned on RACE dataset, and compared it with the fine-tuned model (Fig. 4). Furthermore, we quantified how the properties of DNN attention changed throughout the fine-tuning process by analyzing models that received different steps of fine tuning. The steps we sampled were exponentially spaced between 1 and the maximum fine-tuning steps.
DNN attention

In each attention head, the attention mechanism calculated an attention weight between any pair of inputs, either words or special tokens. The vectorial representation of each input was then updated by the weighted sum of the vectorial representations of all inputs\(^1\). In other words, the models we considered were all context-dependent models, in which the representation of each word was modeled by integrating the representations of all inputs. Since only the CLS token was directly related to question answering, here we only considered the attention weights that were used to calculate the vectorial representation of CLS (illustrated in Fig. 1d). For each layer, the output of a attention head was computed using the following equations. For the sake of clarity, we denote the input words and tokens generally as \(X_i\).

\[
C^h = \sum_{i=1}^{N+M+2} \alpha_i V_i = \alpha_c V_c + \sum_{n=1}^{N} \alpha_p V_{pn} + \alpha_s V_{s1} + \sum_{m=1}^{M} \alpha_m V_{om} + \alpha_s V_{s2},
\]
\[
\alpha_i = \frac{\exp(Q_i K_i^T)}{\sum_{i=1}^{N+M+2} \exp(Q_i K_i^T)},
\]
\[
V_i = X_i W^v + b^v, \quad K_i = X_i W^k + b^k, \quad Q_c = X_c W^q + b^q,
\]

where \(W^v, W^q, W^k, b^v, b^q, \text{ and } b^k\) were parameters to learn from the data. The attention weight between CLS and the \(n\)th word in the passage, i.e., \(\alpha_{pn}\), was compared to human attention. Here, we only considered the attention weight associated with the correct option.
Output of the attention module, i.e., $C^0$, was concatenated over all the 12 heads in each layer, and further processed by position-wise operations to generate the final representation of CLS in the layer$^{17}$. Additionally, DNN used byte-pair tokenization which split some words into multiple tokens. We converted the token-level attention weights to word-level attention weights by summing the attention weights over tokens within a word$^{21,24}$.

**Human attention prediction**

We analyzed eye fixations during passage reading in Study 1 and the first-pass passage reading in Study 2. For each word, the total fixation time was the sum of the duration across all fixations that fell into the square area the word occupied. We averaged the total fixation time across all participants who correctly answered the question, and measured human attention using the attention density, i.e., the total fixation time divided by the area a word occupied.

We employed linear regression to test whether a set of features could explain human attention distribution. Four sets of features were analyzed, i.e., textual features, layout features, task relevance, and DNN attention weights. The textual features included word length, logarithmic word frequency estimated based on the British National Corpus$^{47}$, ordinal position of a word in a sentence, ordinal position of a word in a passage, and ordinal sentence number of a word. The layout features referred to the visual layout of text, i.e., features induced by line changes, including the coordinate of
the left most pixel of a word, ordinal position of a word in a paragraph, ordinal row number of a word in a paragraph, ordinal row number of a word in a passage. Task relevance was annotated by humans, and the DNN attention weights included the 144 attention weights from all layers and attention heads. In the regression analysis, human attention density was modeled using the following equation.

\[
attention\_density_{w} = \sum_{j=1}^{J} \beta_{j} F_{w,j} + b + \varepsilon_{w},
\]

where \( F \) and \( \varepsilon \) denoted the features being considered and the residual error, respectively. The parameters \( \beta \) and \( b \) were fitted to minimize the mean square error.

Each feature and the human attention distribution were normalized within a passage by taking the z-score. The prediction accuracy, i.e., the correlation between predicted attention and actual human attention, was calculated based on five-fold cross-validation. Each question type was separately modeled.

**Statistical tests**

We employed a one-sided permutation test to test whether the attention distribution predicted by a set of features significantly correlated with human attention. Five hundreds of chance-level prediction accuracy was calculated by predicting shuffled human attention. Specifically, the human attention density, i.e., unit fixation time, was shuffled across words and was predicted by word features which were not shuffled.

The procedure was repeated 500 times, creating 500 chance-level prediction accuracy. If the actual correlation was greater than \( N \) out of the 500 chance-level correlation, the significance level was \((N + 1)/501\).
The comparison between global and local questions were based on bias-corrected and accelerated bootstrap\(^4\). For example, to test whether the prediction accuracy differed between the 2 types of questions, all global questions were resampled with replacement 5000 times and each time the prediction accuracy was calculated based on the resampled questions, resulting in 5000 resampled prediction accuracy. If the prediction accuracy for local questions was greater (or smaller) than \(N\) out of the 5000 resampled accuracy for global questions, the significance level of their difference was \(2(N + 1)/5001\). When multiple comparisons were performed, the p-value was further adjusted using the false discovery rate (FDR) correction.

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**Author contributions**

Nai Ding acquired the funding, conceived and coordinated the project, analyzed data, and wrote the manuscript. Jiajie Zou implemented the experiments and models, analyzed data, and wrote the manuscript.
Competing interests

The authors declare no competing interests.

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Supplementary information

Deep Neural Networks Evolve Human-like Attention Distribution during Reading Comprehension

1. Supplementary Tables

2. Supplementary Figures
1. Supplementary Tables

Table S1 | Hyperparameters for fine-tuning DNN on RACE. We adapted these hyperparameters from reference\(^1\text{-}^4\).

| models  | learning rate | training steps | training batch size | weigh decay |
|---------|---------------|----------------|---------------------|------------|
| BERT    | 1e-5          | 27455          | 16                  | 0          |
| ALBERT  | 2e-5          | 12000          | 32                  | 1000       |
| RoBERTa | 1e-5          | 21964          | 16                  | 1200       |

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2. Supplementary Figures

**Word Length vs Total Fixation Time**

![Graph showing the relationship between word length and total fixation time. Error bars represent 1 standard error of the mean across participants. Word length is counted by letters.]

**Fig. S1 | The relationship between word length and the total fixation time on the word.** Error bars represent 1 standard error of the mean across participants. Word length is counted by letters.
Influence of Fine-Tuning on DNN Attention and Task Performance

**Influence of task on DNN attention**

Each dot denotes a fine-tuning step (color coded). Plots from the left to the right denote the results for layer 1 to layer 12. The fine-tuning process modulates the attention properties in deep but not shallow layers of DNN: It enhances the sensitivity to top-down task relevance while reducing the sensitivity to low-level textual features, which correlates with the increase in task performance.