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Bachelor's thesis

Difference in Mind Attribution of ChatGPT in Scientific Articles in Comparison to Media Articles

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Abstract

When humans interact with AI systems, they attribute different mental states (beliefs, feelings, and expectations) to the AI system, and even anthropomorphise it. This process is called mind attribution. This Bachelor's thesis explores, whether there is a difference in mind attribution towards ChatGPT in scientific papers compared to media articles. Language analysis will be applied to a collection of scientific papers and a collection of media articles and Mind Perception Dictionary verbs, as well as Mental Physical Verb Norms, will be counted and analysed to deduce the level of mind attribution. Based on the Mental Physical Verb Norms, scientific papers attribute more mind towards ChatGPT than media articles. The use of the Mind Perception Dictionary indicates that scientific articles attribute more mind than media articles, even though these findings are not statistically significant. The findings clearly show: The Mind Perception Dictionary and the Mental Physical Verb Norm scale need more differentiation and refinement in the context of AI systems, as the exact meaning of each dictionary word needs to be evaluated in the context of AI.

Kurzfassung

Bei der Interaktion mit Künstlicher Intelligenz projizieren Nutzer verschiedene Erwartungen und Gefühle auf die Künstliche Intelligenz, sie schreiben der KI sogar menschenähnliche Attribute zu. Dieser Prozess nennt sich Mind Attribution (aus dem Englischen). Diese Bachelorarbeit untersucht, ob wissenschaftliche Artikel ChatGPT ein anderes Ausmaß an Gewissen zuschreiben als Artikel in den freien Medien. Dies wird mit einer Sprachanalyse und den Konzepten, die dem Mind Perception Dictionary und der Mental Physical Verb Norm Skala zugrunde liegen, untersucht. Mithilfe der Mental Physical Verb Norm Skala wurde festgestellt, dass wissenschaftliche Artikel ChatGPT mehr Gewissen zuschreiben als Artikel in den freien Medien. Die Ergebnisse des Mind Perception Dictionary deuten ebenfalls darauf hin, jedoch sind diese Ergebnisse statistisch nicht signifikant. Durch die Ergebnisse wird klar: Die Einträge des Mind Perception Dictionary und der Mental Physical Verb Norm Skala müssen in Bezug auf Künstliche Intelligenz neu bewertet und angepasst werden, da viele Verben in Bezug auf Künstliche Intelligenz eine andere Bedeutung haben.

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1 Introduction and Motivation

The advance of Artificial Intelligence is significant within recent years [20]. The emergence of ChatGPT [14] has been widely reported, capturing the public's attention as being the fastest online platform to gain one million users in history [15]. It took ChatGPT five days. Released in November 2022, the ChatGPT website is used around 600 million times a month [30].

With the capability of solving all kinds of different tasks, creating fitness exercise plans, generating whole plots for short movies, or solving entire tasks for school homework, ChatGPT sometimes generates ridiculously wrong answers. Many people are wondering, if ChatGPT is so capable of performing different tasks, why can prompts sometimes be answered so wrong [40], even making up facts that never happened [42][9]? Some start to wonder, what is the most suitable term for ChatGPT [40]? Is it Artificial Intelligence? An algorithm? An automated system? A robot? A large language model? Just a computer program? [3]

Langer et al. [18] discovered that the specific terminology used to describe a piece of software within the realm of Artificial Intelligence can lead to varying users' assumptions about its capabilities and functions, solely based on the term. Additionally, the users' perception, expectations, and level of anthropomorphism vary based on the term used to describe the software. Anthropomorphism in general is the act of attributing human-like traits to other humans [20] or other non-human entities. Concerning Artificial Intelligence, users infer certain mental pictures, expectations, thoughts, and biases towards these systems based on the description given.

With the help of Mental-Physical Verb Norms (MPVN) [24] and the Mind Perception Dictionary (MPD) [31] natural language can be analysed to explore how much an individual attributes different mental states (beliefs, desires, intentions, and feelings) to self and others. This central human process is called mind attribution [10]. It is not limited to non-human entities like animals or fictional characters, but can also be applied when talking about computer programs and AI technology.

This Bachelor's thesis investigates the extent of mind attribution towards the large language model ChatGPT by scientists compared to media authors. To deduce the level of mind attribution for scientists, scientific papers will be analysed. For the level of mind attribution towards ChatGPT by authors in the media, news articles will be analysed. In the analysis, the use of MPVN and MPD words will be counted and interpreted. The purpose is to evaluate, which level of mind is attributed towards ChatGPT and thus to examine, whether there is a difference in the level of mind attribution between scientific papers and media articles.

2 Related Work

Langer et al. [18] conducted two studies to determine if various terms influence users' perceptions of the same algorithmic decision-making machine (ADM). The following approach was used: Each survey participant was presented with different sentences about ADMs. For different participants, the sentences were the same, only the name for the ADM within the sentence differed. Participants were also given some of the 10 different terms randomly and were then asked for their perception of properties concerning the given term. The questions afterwards probed for perceived tangibility, complexity, controllability, familiarity, anthropomorphism, and machine competence. In their study, anthropomorphism refers to perceiving the given term as an entity possessing human-like characteristics. Their findings revealed that humans project very different mental pictures, expectations, biases, and thoughts onto the same ADM when merely the describing term varies. In their findings, the terms "robot" and "computer" are perceived as more tangible, familiar, and controllable than the term "artificial intelligence" when describing the same ADM. Also, computers and computer programs were perceived as less complex and were less anthropomorphized than artificial intelligence. Computers, computer programs, and artificial intelligence were perceived with relatively high machine competence compared to other terms. Therefore using the appropriate term for an ADM, the level of mind attribution and anthropomorphism by the user could be altered or manipulated. Due to the higher perceived competence of artificial intelligent systems, these systems could be used for tasks they were not built for and fatal errors could occur. These human-made projections did not correlate with the user's education, race, age, or gender but rather with their technological affinity, as participants with higher affinity could differentiate the used terms better. Also, participants with higher technological affinity perceived ADMs as less complex and more familiar and were less likely to anthropomorphize these systems. Interestingly, these differences in expectations and projections were only made by the participants, when talking about different terms for the same ADM. Comparing all the terms to a human manager, participants viewed the ADM terms as similar and were only contrasting between human and non-human entities. The scientists concluded, that users' biases, perceptions, and expectations can be very subjective to different ADM terms, leaving quite a potential to alter and/or manipulate the user's view of the ADM machine. This Bachelor's thesis plans to exploit these findings and the contrast mind attribution of the scientists and the broad media, as the technical affinity between those two entities differs.

The attribution of mind can be observed through various methods, as outlined by Schweitzer and Waytz [31]. Attribution of mind can be measured with the help of surveys. After a given interaction between a participant and another human or non-human entity, participants complete a questionnaire. With this approach, two issues arise: Interactions have to be planned and instructed within certain environments, which can alter the actual results. Furthermore, participants could understand the questions in the survey differently, or the survey just could not grasp the important nuances that the participants perceive. Another approach is monitoring the activity of the precuneus/posterior cingulate cortex of the participant, as this region in the brain shows higher activity levels when humans are interacting with other humans or entities with perceived minds [39]. This brain monitoring can only be performed in a laboratory, which brings up the already mentioned issue of planned and instructed interactions within certain environments. Thus Schweitzer and Waytz favor the help of language as a vehicle to capture people's perception of other entities and mind attribution. Therefore a Mind Perception Dictionary (MPD) with words that ascribe the mind was created. Within several studies [31] they have found significant results. They found out, that the more an individual perceives a mind within the conversational counterpart, the higher the use of mind words. This occurrence is not limited to communications with another human entity. Comparing the description of an insect with the description of a primate within scientific articles, a higher frequency of mind words is used when describing the primate. These findings are supported by studies comparing reviews on Amazon for a basic vacuum cleaner versus an "intelligent" self-moving vacuum cleaner. Even in this realm, the reviewers used more mind words describing the "intelligent" vacuum cleaner. A very interesting conclusion was drawn: If humans describe a friend, they use more mind words than when talking about an acquaintance. No studies were made yet, whether a relationship between a human and another entity can be manipulated with the higher use of mind words. The scientists Orr and Gilead [24] argue that existing dictionaries, such as the MPD, were compiled predominantly based on expert assessments, potentially ignoring words that are more commonly used in daily conversations. In their opinion, the MPD lacks a consensus of language users. Thus, they constructed a dictionary of Mental Physical Verb Norms, that consists of 250 verbs out of the 5000 most used verbs in the English language. In a study with 120 native English-speaking participants, they let them evaluate these verbs on a scale from one to one hundred. The lower the number on the scale, the more physical and less mental the participant perceived the given verb, the higher on the scale, the less physical and the more mental.

Analysing language in explainable AI papers is a measure to quantify mind attribution. Susanne Hindennach et al. found, when referring to Artificial Intelligence, mind attribution can be divided into three different groups: Metaphorical Mind attribution, attribution of awareness, and attribution of agency[10]. "Learning" in the context of AI is used metaphorically, as it describes a procedure where a computer is incorporating new data. "Learning" is therefore not equal within a human context where it means to "gain knowledge by studying" [19]. These findings might suggest limitations of the Mind Perception Dictionary or the Mental Physical Verb Norms in the context of AI. "Learn" does not exist in the MPD but ranks very high on the MPVN scale with a score of 85. According to the MPVN scale, "learn" is, therefore, a highly mental verb and ascribes mind to an entity. After presenting the results of this thesis, it will be discussed, whether the MPVN scale or the MPD in conjunction with the findings of Hindennach et al. prove to be suitable tools to use in the context of AI.

In numerous studies, mind perception, anthropomorphism, and expectations regarding AI technologies have been evaluated using questionnaires and language analysis. However, a comparative analysis of the mind attribution towards ChatGPT in scientific papers and media articles has not been conducted. This will be explored within this Bachelor's thesis.

3 Approach and Methods

3.1 Creation of both article collections

Following extensive research of the literature, the first task involved the creation of two collections, the scientific papers and the media articles. These had to be approximately the same size regarding sentence count to make them comparable.

3.1.1 Creation of the scientific paper collection

40 recent articles about ChatGPT were the benchmark to meet, as this number was also used by Schweitzer and Waytz for comparing mind attribution in articles about insects and primates [31]. These 40 articles were divided into three groups: 10 papers by OpenAI (the company behind ChatGPT), 10 papers by universities where one of the authors was affiliated with a big company, and 20 papers by universities where no author was affiliated with a big company. This ratio was chosen as it roughly matched the ratio of total available articles about ChatGPT on OpenAI's website [29] and on the platforms ACM Digital Library [1], Scopus [36] and IEEE Xplore [12].

Criteria for scientific papers by OpenAI

The 10 papers were downloaded from OpenAI's publication section [29], applying the filter "Publication". These were accessed on October 2, 2023, sorted by date and in English. The keyword "GPT" was used instead of "ChatGPT" due to the latter yielding no results. The difference between ChatGPT and GPT is, that GPT is the large language model (LLM) developed by OpenAI, that gives the AI the ability to generate text. It is trained on terabytes of data from the internet [5]. (ChatGPT is the application optimized for chat interactions, that uses GPT to create responses. ChatGPT is specifically trained for textual conversations.) In their research publications, OpenAI reports on their technical advancements of GPT. ChatGPT, which is a derivative application that is optimized and trained for textual conversations, inherently incorporates these advancements as it uses GPT to create responses. Thus the improvements in GPT are elemental to the functionality of ChatGPT. As a result, OpenAI's research on GPT advancements implicitly encompasses those relevant to ChatGPT. While there is a notable distinction between GPT and ChatGPT, the use of "GPT" as a keyword does not significantly impact the context of this thesis and thus justifies the use as a keyword instead of "ChatGPT". Given that enhancements of GPT directly translate to improvements in ChatGPT, the level of mind attribution towards GPT is correlated with the level of mind attribution towards ChatGPT.

Criteria for scientific papers by universities

To access the 20 papers by universities, the online platforms ACM Digital Library [1], Scopus [36], and IEEE Xplore [12] were used. On the day of download (October 2, 2023) a total of 844 papers with "ChatGPT" were found across the three platforms (6% were from ACM Digital Library, 81% Scopus, 13% IEEE Xplore). To match this ratio, it was decided to use two papers from the ACM Digital Library, 16 from Scopus, and two from IEEE Xplore. The papers were sorted from new to old and had to fulfill the following criteria: All papers had to be in English and accessible through the University Stuttgart as a PDF file. The search keyword was "ChatGPT". They had to be released on November 30, 2022 (release date of ChatGPT) or newer. No other name of an AI system and no reference to another AI system in the title was allowed. No author had to have an affiliation with a company, but affiliations with hospitals were allowed. The affiliation of authors was checked by hand and not with the help of a filter, as the metadata often was not sufficient.

Criteria for scientific papers by companies

The same criteria of the university papers were applied with one difference: whenever an author was affiliated to a company, the paper was added to the companies collection. Doing this procedure, only seven papers were found with affiliation to companies. The last three papers, meeting the same criteria and having an author affiliated with a company, were collected from NeurIPS [23]. NeurIPS is a machine learning conference held every December with the disciplines of machine learning, statistics, artificial intelligence, and computational neuroscience. Major advancements in the AI field are presented here. Thus NeurIPS was chosen to supplement the collection of company papers. In the 10 papers, authors are affiliated with companies like Microsoft [22], Alibaba [2], Tencent [37], Facebook (Meta) [28] and JPMorgan Chase [16], just to name a few.

3.1.2 Creation of the media article collection

To compile the collection of media articles, a list created by PressGazette [21] was used. Every month PressGazette ranks the biggest news websites in the world based on Similarweb data. Similarweb [41] factors in the number of users, number of clicks, reading times, and number of active users. PressGazette is a British trade magazine focusing on journalism and the press [26]. The ranking of November 29, 2023, was used. The articles had to fulfill the following criteria: All articles had to be written in English and searchable with the Python API DuckDuckGo_search [7] and each search had to return more than 10 results per news website. The articles had to be released on November 30, 2022 (release of ChatGPT) or later and be accessible for free with no anti-bot or anti-scraping measures. They had to have the search keyword "ChatGPT" in the title ("intitle:ChatGPT"), and no other AI system names were allowed in the title (for example "Watson", "Bard", "Claude"). Every article had to be downloadable with requests [27] and processable with BeautifulSoup4 [4].

News articles from the following sites fulfilled these requirements: bbc.co.uk, bbc.com, cnn.com, edition.cnn.com, forbes.com, foxnews.com, nbcnews.com, news.yahoo.com, nypost.com, the-guardian.com, the-sun.com, thesun.co.uk, usatoday.com, news18.com. With the help of a self-written Python script, the links to the media articles were searched with DuckDuckGo_search and added into a .txt file for each news site. It was chosen to use DuckDuckGo_search, as the API was easy to use, and results could be requested for a specific period. Also, no political bias and no compensation (except for so-marked ads) influence the rankings of search results [6]. The easy and objective way was the reason to use DuckDuckGo. The Google search engine was also considered to be used with the Google developer tools. As the implementation was more cumbersome compared to DuckDuckGo_search and the requests per day via the API are limited (thus not scalable), this idea was discarded. It was also questionable, how search results are ranked by Google, including metadata, SEO ranking, and paid advertisement.

A conservative approach using time delays and dummy requests for the DuckDuckGo_search was necessary, to avoid rate limits and thus being denied of further requests. The results of the DuckDuckGo_search in the form of URLs are downloaded using the Python library requests. Each URL request is then parsed with the HTML parser BeautifulSoup4, where the headline and the article body (soup.find('article')) are extracted. If an article is for some reason not processable or does not meet the criteria mentioned before, it is sorted out. DuckDuckGo_search returned 799 URLs across the 14 news websites. 88 URLs or their respective articles did not meet the criteria above and were filtered out, thus resulting in 711 articles in total for the media article collection. The check for English language was done with the langdetect [17] Python library, which directly uses Google's language-detection library [8] from Java to Python [17]. All media articles that fulfilled the criteria were appended to a .txt file so that in the end for each media news site all articles were within a document. The download of the articles was also done with a conservative approach with time delays of five seconds, to avoid being banned.

3.2 Processing of both collections

With the Bash (Linux Shell) script pdftotext from the poppler-utils library [25] all the scientific papers were converted from PDF to .txt files. As the media articles were already downloaded as .txt files, no conversion was necessary. Afterwards, a script by Mehroz Khan [11] was used to clean up all .txt files of the scientific papers. Everything in between the abstract and the references of the paper is kept, anything else is deleted. The media article files were cleaned up with another script where all new lines, emojis, and non-English characters were removed. After renaming the scientific papers and media articles, both collections were ready to be analysed. In the next paragraph, the analysis steps will be explained briefly. The results of the intermediate steps and the final results will be found in Chapter 4. Two Jupyter Notebooks were used to process the collections, one for the scientific papers, and the other for the media articles. This was done as both collections had different sizes (scientific papers: 40 papers, media articles: 711 articles from 14 different news sites, thus 14 different documents for the media articles). Using the spaCy model "en_core_web_sm", the number of sentences were counted per paper or news site respectively to figure out the total number of sentences per collection and thus collection size. Each document is loaded and analysed by spaCy. Then the number of occurrences of MPD words and MPVN were counted that reference ChatGPT (or a variation). The exact code can be found in the following listing. The instances of the gptkeywords array can be found in Section 3.2.1.

```
#Part of speech tagging
for possible_subject in doc:
   if possible_subject.dep == nsubj and possible_subject.head.pos == VERB:
      noun=possible_subject.lemma_
      verb=possible_subject.head.lemma_
      if noun.lower() in gptkeywords:
         nouns.append(str(noun).lower())
         verbs.append(str(verb).lower())
```

The results of the occurrences of MPD words and MPVN are stored within arrays. With these results, the analysis began. It was counted how many sentences were found, where “ChatGPT” (and variations) was the subject. For media articles in total, for the scientific articles in the three different groups (OpenAI, Big Companies, Universities) and in total as well. Also, the total number of MPD and MPVN for all mentioned groups was counted. For the MPD words a MPD ratio or frequency was calculated, by dividing the number of MPD matches per group by the number of sentences, where “ChatGPT” (and variations) was the main noun. With the MPVN results, the median MPVN score and standard deviation per document were calculated.

Furthermore, the aforementioned processing was also done for the headlines of the media articles. Here, only the headlines were analysed by spaCy.

3.2.1 Keyword array to match

The subjects of each sentence were matched with the following words: “ChatGPT-3”, “ChatGPT-3.5”, “ChatGPT-4”, “ChatGPT-4.0”, “ChatGPT”, “ChatGPT3”, “ChatGPT3.5”, “ChatGPT4”, “ChatGPT4.0”, “GPT-3”, “GPT-3.5”, “GPT-4”, “GPT-4.0”, “GPT3”, “GPT3.5”, “GPT4”, “GPT4.0”, “GPT”.

4 Results

This chapter delineates all findings and results of the analysis. First, the results of the scientific papers will be examined, followed by the media articles. Afterwards, a comparative analysis of both will be presented.

In the collection of the 40 scientific papers, spaCy identified a total of 18,515 sentences. When looking into the three different groups, the company group is 6,232 sentences large, the collection by OpenAI papers consists of 7,012 sentences and the university paper collection consists of 5,271 sentences. To form a correct sentence in English, at least one verb is needed. In the counting process, verbs that reference the main noun of a sentence are analysed, so the size of the collections is based on sentence count rather than word count. Across the three groups, a total of 938 sentences were found where the main noun matched the target word list (see target word list in section 3.2.1). The company group amounted to 432 gptkeyword sentences, the OpenAI group contained 173 sentences, and for the university group, 333 sentences were found.

In the collection of the 14 different news websites, spaCy identified a total of 28,774 sentences. Across the 14 news websites, a total of 1,635 sentences were found where the main noun was in the gptkeyword array (see gptkeyword array in section 3.2.1).

4.1 MPD results

Given the thesis's exploration of mind attribution towards ChatGPT, it is interesting how often a MPD word is used referring to ChatGPT. To put those results in perspective with each other, the MPD frequency or ratio is calculated by dividing the number of MPD occurrences by the number of sentences, where ChatGPT is the main noun.

The analysis revealed 33 occurrences of MPD words within the scientific paper collection. 21 MPD occurrences in the company group, two occurrences in the OpenAI group, and 10 occurrences in the university group. All the individual results can be found in table 4.2, where the individual results per group for the scientific papers, the cumulated result, and the results of MPDs for the media article collection can be found. A total of 21 occurrences of MPD words were found in the media article collection. No analysis between the different news websites was made concerning the MPD frequency, as the number of articles per news website differed significantly and is not the focus of this thesis.

4.1.1 MPD frequency

The following table 4.1 shows the MPD frequencies divided into the scientific papers and the media articles. The scientific paper results are further divided into the three groups (companies, OpenAI, and universities). The MPD frequency is calculated by dividing the number of MPD matches by the number of ChatGPT sentences (whenever the subject is a target word).

	Number of MPD matches	**Number of ChatGPT sentences**	**MPD frequency**
scientific papers			
total	33	938	3,52%
companies	21	432	4,86%
OpenAI	2	173	1,16%
Universities	10	333	3,00%
media articles			
total	21	1,635	1,28%

Table 4.1: MPD frequency - scientific papers

Looking at the MPD frequencies per group for the scientific papers, it appears that the company group attributes the most mind towards ChatGPT as this group has the highest MPD frequency. Comparing those results against each other within the scientific collection, the Kruskal-Wallis test needs to be used, as more than two different groups are compared with each other, and the MPD words are not normally distributed. The null hypothesis states the absence of any significant differences among the various groups (companies, OpenAI, universities). The alternative hypothesis is, that there is a difference between the different groups. Utilizing the Kruskal-Wallis test in Python [33] yielded the following results: statistic=2.8739, p-value=0.2377. As the p-value is not less than 0.05, the null hypothesis cannot be rejected and the results are not statistically significant. Based on counting the MPD words, there is no statistically significant difference in mind attribution between the company collection, OpenAI research papers, and the papers written by scientists in universities.

4.1.2 Individual MPD verb results

The following table 4.2 shows the results of the MPD matches in total and per group for the scientific papers and the media article collection. The scientific total column cumulates the MPD matches of the other groups for each MPD word. One MPD word stands out - “understand”, making up almost 40% of the number of matches in the scientific collection.

MPD word	scientific companies	scientific OpenAI	scientific universities	scientific total	media total
understand	9	1	3	13	3
suffer	3	0	1	4	0
predict	4	0	0	4	3
recognize	1	0	2	3	3
communicate	2	0	0	2	0
accept	0	1	1	2	0
memorize	1	0	0	1	0
prefer	1	0	0	1	0
enjoy	0	0	1	1	0
realize	0	0	1	1	1
care	0	0	1	1	1
think	0	0	0	0	3
fascinate	0	0	0	0	2
experience	0	0	0	0	1
hurt	0	0	0	0	1
judge	0	0	0	0	1
concern	0	0	0	0	1
feel	0	0	0	0	1
sum:	**21**	**2**	**10**	**33**	**21**

Table 4.2: MPD results for the scientific and media collection, entries represent the number of MPD matches

4.1.3 MPD results - comparison of scientific papers and media articles

The MPD ratio for the scientific papers is 3.51%, the MPD ratio for the media articles is 1.28%. Comparing these results, the MPD ratio of the scientific papers is more than double the MPD ratio of the media articles. This implies a greater degree of mind attribution towards ChatGPT in scientific papers and thus scientists attributing more mind towards ChatGPT compared to media articles. Checking these findings statistically, the Mann-Whitney-U-Test needs to be used, as two independent groups are compared, and the values are not normally distributed. The null hypothesis is, that there is no difference between the two groups (scientific papers and media articles). The alternative hypothesis is, that there is a statistical difference between the two groups. Using the Mann-Whitney-U test in Python [34], the following results are found: statistic=235.0, p-value=0.3294. As the p-value is not less than 0.05, the null hypothesis cannot be rejected and the results are not statistically significant. Based on counting MPD words, there is no statistical difference in mind attribution between the scientific papers and the media articles.

4.2 MPVN results

As the collections were the same as for the MPD words analysis, all the results in regards to collection size (sentence count per collection and respective group and the number of sentences where ChatGPT was a target word) were the same. These results can be found at the beginning of Chapter 4. In the scientific papers, a total of 530 MPVN were referencing ChatGPT (or a variation). 259 MPVNs were found in the company papers, 94 in the OpenAI papers, and 177 in university papers. A total of 1,018 MPVNs that reference ChatGPT (or a variation) were found within the media article collection. No analysis between the different news websites was made concerning the MPVN score, as the number of articles per news website differed significantly and is not the focus of this thesis.

4.2.1 MPVN score

In the following sections, the phrase MPVN score will come up. The MPVN score represents the ranking of a verb on the MPVN scale. When talking about whole collections, the MPVN score is the mean of all the MPVN scores of the individual verbs. As the three different groups (companies, OpenAI, universities) for the scientific paper had different sizes, it is not sufficient to calculate the mean of means. Thus the total mean for the scientific papers was calculated separately. The mean for the media collection was calculated across the 14 news websites.

In table 4.3 the MPVN results of mean and standard deviation (SD) can be found. The mean in total or for each group is representative of the MPVN score on the MPVN scale from zero to 100. The higher the score for a group, the more mental the used verbs are and therefore the higher the mind attribution.

Mean and SD	**Mean**	**SD**
scientific papers		
total	44.83	20.19
companies	43.32	19.38
OpenAI	52.73	20.31
universities	42.85	20.29
media articles		
total	40.77	19.33

Table 4.3: MPVN results scientific papers - Mean and SD

Observing the data in table 4.3, the standard deviation is almost identical for each group. It appears, that OpenAI papers use more mental verbs and thus attribute more mind towards ChatGPT. Checking these findings statistically, a one-way ANOVA needs to be used, as more than two independent groups are compared, and the values are normally distributed. The null hypothesis is, that the group means are equal. The alternative hypothesis is, that there is a statistical difference between the means of the different groups. Using the one-way ANOVA in Python [32], the following results are found: statistic=9.015, p-value=0.000141. As the p-value is less than 0.05, the null hypothesis can be rejected and the results are statistically significant. So it is proven that OpenAI uses more mental verbs compared to the other two groups and thus attributes more mind towards ChatGPT than the others.

When looking at the graph 4.1, the higher MPVN score can be easily explained: out of the 94 MPVN, only four verbs stand out due to number of occurrences: “perform”, “achieve”, “improve”, and “learn”. Every other counted MPVN occurrence is lower than five. The high number of occurrences for “achieve”, “improve”, and “learn” in the OpenAI group drive the higher mean MPVN score. The other graphs for the companies (7.2) and the universities (7.4) are found in the appendix.

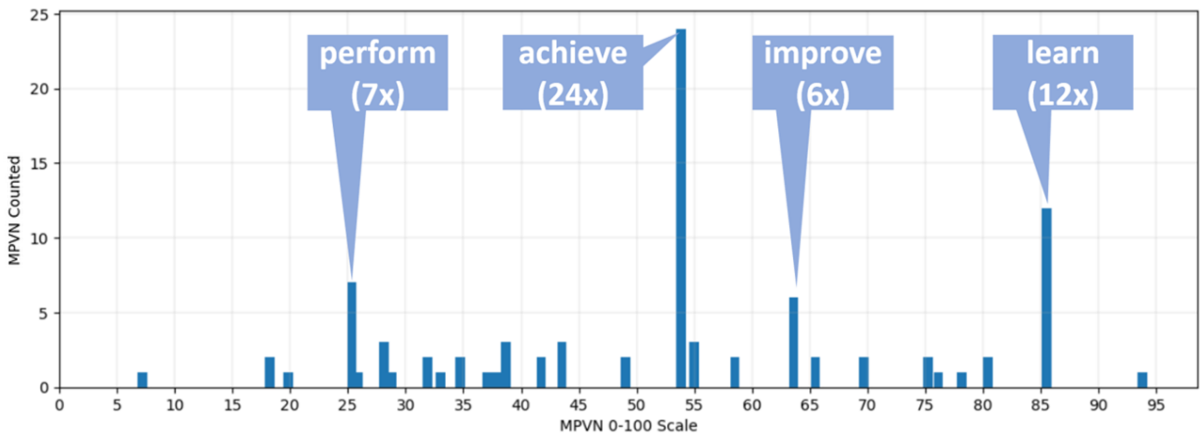

Figure 4.1: Counted MPVN on the MPVN scale - scientific papers, OpenAI group

4.2.2 Individual MPVN results

In table 4.4 a part of the MPVN results are shown. For the mentioned table, the decimal digits of MPVN scores were cut off, as the exact value is not necessary for this representation and thus the provided score is sufficient. The MPVN are still ordered in the table according to the MPVN scale. In the scientific companies column, all verbs with more than five matches (also indicated in the table header) are shown. The same applies to the OpenAI and the university column. In the scientific total column, all the MPVN occurrences with more than 10 matches are shown across all three groups. In the media total column, the MPVN occurrences with more than 10 matches for the media article collection are shown.

MPVN	MPVN score	scientific companies (> 5)	scientific OpenAI (> 5)	scientific universities (> 5)	scientific total (> 10)	media total (> 10)
go	16					30
come	17					24
make	18	7				52
get	19					19
take	19					30
perform	25	18	7	14	39	11
give	25					26
write	27	6		7	13	38
use	28	7		6	16	20
show	33	7		10	18	
replace	33					12
work	34	6				14
pass	35					18
help	35	18		7	25	52
provide	37	24		20	45	40
produce	38	7			15	24
say	38					39
tell	43					16
respond	49					33
create	52					28
offer	53			6	11	17
achieve	53	8	24		34	
answer	54					20
change	57					18
improve	63		6		14	
become	63	10			11	46
prove	66					11
suggest	72					11
learn	85		12		15	
know	92					18
understand	93	9			13	

Table 4.4: MPVN results for the scientific and media collection, entries represent the number of MPVN matches

4.2.3 MPVN results - comparison of scientific papers and media articles

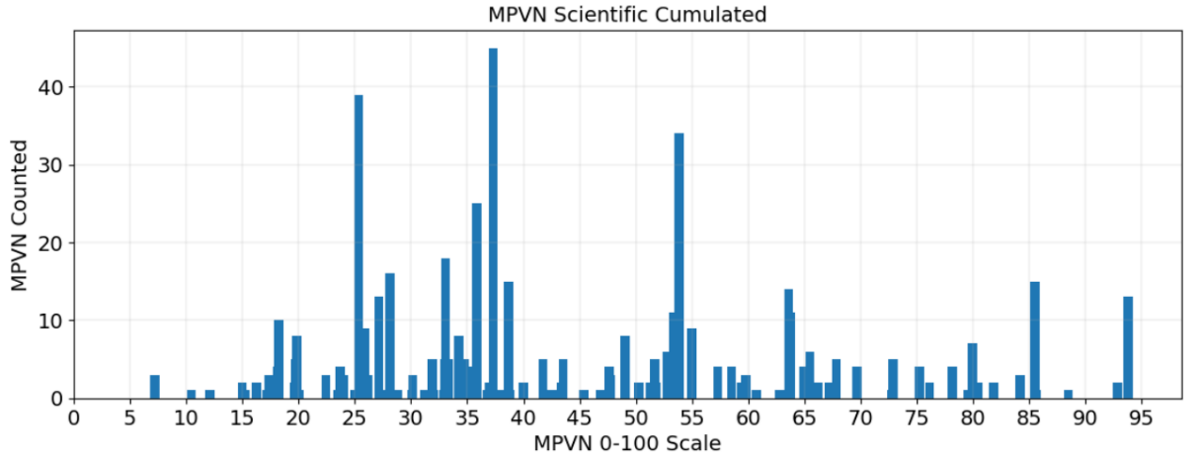

Figure 4.2: Counted MPVN on the MPVN scale - scientific papers in total

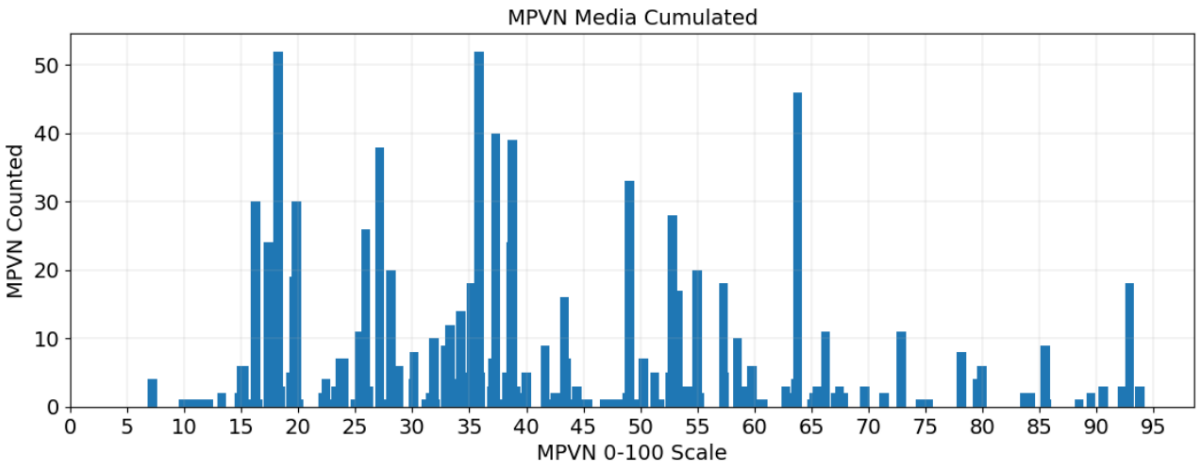

Figure 4.3: Counted MPVN on the MPVN scale - media article in total

The mean MPVN score for the scientific papers is 44.83, and the MPVN score for the media articles is 40.77. As the MPVN score is a calculated mean, looking at both graphs 4.2 and 4.3, the lower mean is explainable with the high cumulation of verbs with a MPVN score between 18 and 40, which bring down the score. Comparing both results, the mean MPVN score of the scientific papers is higher than the mean MPVN score of the media articles. This would imply that the scientific papers and thus the scientists attribute slightly more mind towards ChatGPT than the media articles and thus ordinary people. Checking these findings statistically, the t-test needs to be used, as two independent groups are compared, and the values are randomly normally distributed with almost equal standard deviation. The null hypothesis is, that there is no difference between the mean of the two groups (scientific papers and media articles). The alternative hypothesis is, that there is a statistical difference of the mean between the two groups. Using the t-test in Python [35], the following results are found: T-statistic value = 3.862, p-value = 0.000116. As the p-value is less than 0.05, the null hypothesis can be rejected and the results are statistically significant. Thus it is statistically proven, that scientists attribute more mind towards ChatGPT based on the MPVN scale.

4.2.4 MPVN analysis with headlines of media articles

As the results were not anticipated by the author (particularly the MPVN results), and a higher mind attribution by the media was anticipated, the same analysis for MPVN was performed by analysing the headlines only. A catchy headline is the first thing a reader sees when accessing online media articles, and thus crucial to drive viewers to the articles. Therefore it was assumed by the author, that a higher level of mind attribution is used in the title compared to the article. With an MPVN score of 36.83 and a standard deviation of 17.12, this assumption could not be validated.

4.3 Comparison of both collections with equal size

The scientific papers collection with 18,515 sentences and the media article collection with 28,774 differed considerably. Therefore a subsequent analysis with a randomized subsample of the media article collection with 18,333 sentences was performed. Here, spaCy found a total of 1,075 sentences where ChatGPT (or a variation) was the main noun of a sentence (scientific papers 938 ChatGPT sentences). 13 MPD matches were found with a MPD frequency of 1.21% (compared to 1.28% for the total media article collection). 700 MPVN were found in the subsample (compared to 1,018), with a MPVN score (mean) of 40.2 (compared to 40.77) and a standard deviation of 19.6 (compared to 19.33). The results of the subsample are very similar to the total sample. With all statistical tests performed with the subsample, all the tests provide the same results concerning the statistically significant findings.

5 Discussion and Future Work

5.1 Discussion

The results of the analysis were not the expected results. The author initially expected media articles to attribute more mind towards ChatGPT. This assumption stemmed from the following reasons: Langer et al. [18] identified, that the technical affinity of an individual is the most relevant factor for projecting different perceptions onto algorithmic decision-making machines (ADM). Participants with higher technological affinity perceived systems more less complex, more tangible, and familiar, ascribed higher machine competence, and were less likely to anthropomorphize the systems. ChatGPT fits into the category of an ADM. Assuming, that scientists writing papers in the field of AI systems have a higher technical affinity with ChatGPT than authors writing articles for news websites, less anthropomorphism and less mind attribution in scientific papers were expected. Furthermore, scientists writing for OpenAI are more involved in the development of ChatGPT. Also here, a lower mind attribution due to an even higher assumed technical affinity was anticipated. On the other hand, it was not factored into the expected results, that being cited and publishing papers is also important for a scientist's career. Writing papers on state-of-the-art technology like ChatGPT and not missing out on the AI hype could have motivated some scientists to exaggerate findings in the context of AI. This was observed by Simone Natale, where in retrospect many claims of scientists in the field of computers turned out to be unrealistic [13]. Focusing on the authors of media articles, it was assumed, that authors had to write up-to-date articles during the fast rise of ChatGPT, where wishful thinking of its capabilities and inappropriate anthropomorphism were included.

A statistically significant difference in mind attribution can be confirmed with the MPVN as a measure. Scientific papers attribute more mind towards ChatGPT than media articles. Examining the last two columns of table 4.4, which display MPVNs with verbs exceeding ten matches, the prevailing MPVN results can be explained. Authors from the media probably access ChatGPT only via the chatbot function on the OpenAI website. In the last column of the table (total media results), many matches are verbs that describe a conversational action (e.g. "write", "say", "tell", "respond", "answer"). In a broader sense, one could see "give", "provide" and "produce" also as a form of conversational action. The only thing ChatGPT can give, provide, and produce is textual responses (dismissing newer features like image creation and other functions), as ChatGPT uses textual output for its answers. Except for the verb "answer", all the mentioned verbs rank at a MPVN score lower than 50. When looking at all the matches (not represented in table 4.4) and sticking to the clear conversational verbs ("write", "say", "tell", "respond", "answer", and "speak"), these verbs make up 6.6% of all matches in the scientific group, but 14.7% for the media group. Again, all these conversational verbs have a MPVN score lower than 50, except for "answer". Due to the higher use of conversational verbs in the media articles and their MPVN score below 50 (except “answer”), the lower MPVN score of the media articles can be explained. These results are further reinforced by the fact, that scientists explain new advancements, technical iterations, and use cases for ChatGPT. So ChatGPT “learned”, “improved” and “achieved” something new, which are all highly mental verbs, that increase the scientific MPVN score even further.

When utilizing the Mind Perception Dictionary, no statistically significant conclusion can be drawn whether there is a difference in mind attribution in scientific articles compared to the media. Thus using the concept of the Mind Perception dictionary, there is no difference in mind attribution between scientists and ordinary people in the media. The Mind Perception Dictionary consists of words that highly ascribe the mind. Very few matches were expected from the beginning. Despite the scientific collection being 35% smaller in size (in terms of sentence count) compared to the media article collection, 57% more MPD matches were identified. When using the randomized subsample comparison for equal collection size, 150% more MPD matches were identified in the scientific collection. This clearly shows the issue brought up by Orr and Gilead[24]: The mind perception dictionary was compiled by scientists and lacks the consensus of people using the English language.

Counting MPD, the analysis is focused only on verbs that highly attribute mind. Using the MPVN scale as a measure, all verbs referencing ChatGPT account for the final score. Even though, the statistical analysis of both methods reveals that the difference in mind attribution is ambiguous between both collections, the MPD findings indicate what is proved with the MPVN: scientific papers attribute more mind towards ChatGPT than media articles. The not significant MPD findings could be explained by the fact, that the MPD was only compiled by experts and only one of the two examined collections was written by scientists. It is disputable, if the Mind Perception Dictionary is the best tool to compare different collections of texts, when some groups are written by scientists and others are not. The significant findings of the MPVN could further indicate, that the Mental Physical Verb Norm scale is more suitable for a greater spectrum of text.

5.2 Limitations and Future Work

In future work, the number of MPD matches could be increased, as currently only a fraction of the MPD is utilized. The MPD not only consists of verbs but also other word types like nouns and adjectives. If a reliable way to find adjectives (or nouns) referencing ChatGPT is found, a larger part of the Mind Perception Dictionary could be put to use. This task can probably be performed using spaCy. Through that, the match count would be increased and results refined. This thesis focuses exclusively on verbs, omitting other word types from the MPD for better comparison with the Mental Physical Verb Norms.

To increase the overall match count of MPVN and MPD, coreference resolution could be included in the counting process in the future. Coreference resolution is the act of identifying all expressions that refer to the same entity within a text [38]. If, for example, ChatGPT (or a variation) is mentioned by an “it” in another sentence, nothing is counted in the analysis process at the moment. Incorporating coreference resolution potentially increases match count and refines the results.

The collections comprised 40 scientific papers and 711 media articles. In the future, both collections could be enlarged. Scientific papers could be crawled and accessed via script, to easily increase the size of the scientific paper collection. The biggest issues when crawling the media articles were paywalls and not processable news sites. Subscribing to premium services or cooperation with news publishers could significantly increase the quantity of crawlable media articles. A different type of parsing with BeautifulSoup could also reduce the number of unprocessable articles. At the moment, only the article body (soup.find('article')) is extracted.

For general application, the Mind Perception Dictionary and the Mental Physical Verb Norm scale are effective and useful without a doubt. In the context of AI systems, more differentiation concerning mind attribution is needed. Hindennach et al. [10] propose, that mind attribution concerning explainable AI can be divided into three groups: Metaphorical Mind attribution, Attribution of Awareness, and Attribution of Agency. Using these findings to refine the existing MPD and MPVN or create a new type of dictionary to analyse mind attribution towards AI systems, probably different results will emerge. This new dictionary must distinguish the meaning of verbs in the context of AI systems. All verbs that attribute metaphorical mind in the context of AI systems need to be evaluated as not attributing a high level of mind. A verb like "learn" would not be assessed as a highly mind-attributing verb but rather identified as a computational process by ChatGPT and thus fits into the Metaphorical Mind Attribution category. The MPD with verb consideration only could be used as a reference point. The meaning of each verb needs to be assessed concerning AI systems. If a verb is still identified as a highly mind-attributing verb, it is appended to the new dictionary and a similar analysis process could be performed. Of course, new verbs that are currently not in the MPD need to be assessed as well. Another possible approach could be the use of a cluster with groups of low, medium, and high mind attribution in the context of AI. Again, the meaning of the individual verbs in the context of AI needs to be assessed. When a reliable evaluation is found, the use of an ordinal scale with several groups could differentiate the groups even further. The implementation of a new dictionary focused on AI mind attribution would probably alter these findings. Assessing verbs that fit into the Metaphorical Mind Attribution category with a low mind attribution value, probably a lower level of mind attribution of the OpenAI and the scientific papers would be found. Upon the development of these new tools, it would be beneficial to replicate the analysis conducted in this thesis in the future.

6 Conclusion

In this Bachelor's thesis, the difference in mind attribution of ChatGPT in scientific papers in comparison to media articles was examined. The difference was measured based on language analysis. Therefore, a collection of 40 scientific papers and a collection of 711 media articles were created and analysed. ChatGPT (and variations of ChatGPT) were identified with spaCy and the referencing verbs were counted and analysed. Two concepts for the analysis were used: the Mind Perception Dictionary and Mental Physical Verb Norms.

Utilizing the Mind Perception Dictionary a higher MPD frequency is found in the scientific papers (3.52%) in comparison to the media articles (1.28%). These findings were statistically not significant. However, they indicate, that scientific papers attribute more mind towards ChatGPT than media articles.

Based on the Mental Physical Verb Norm scale, a statistical difference in mind attribution toward ChatGPT between scientific papers and media articles was detected. Scientific papers have a higher MPVN score (44.83) and therefore attribute more mind towards ChatGPT than media articles (MPVN score of 40.77).

In the scientific papers, the MPD frequency is 2.75 times greater than the MPD frequency observed in media articles. Even though the MPD results are not statistically significant, they indicate what the MPVN results proved: Scientific papers attribute more mind towards ChatGPT than media articles.

7 Appendix

In this last section, a collection of graphs can be found with the results of this thesis.

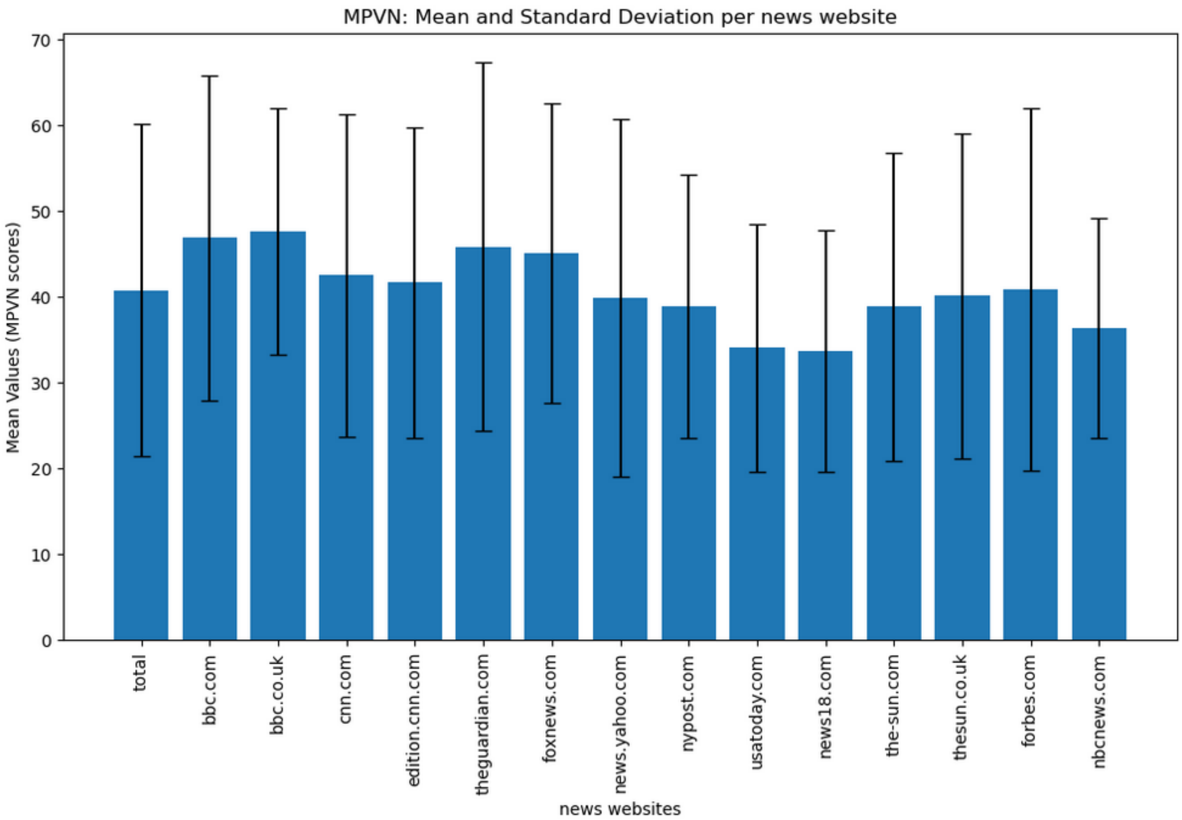

Figure 7.1: Mean values (MPVN scores) and SD per news website

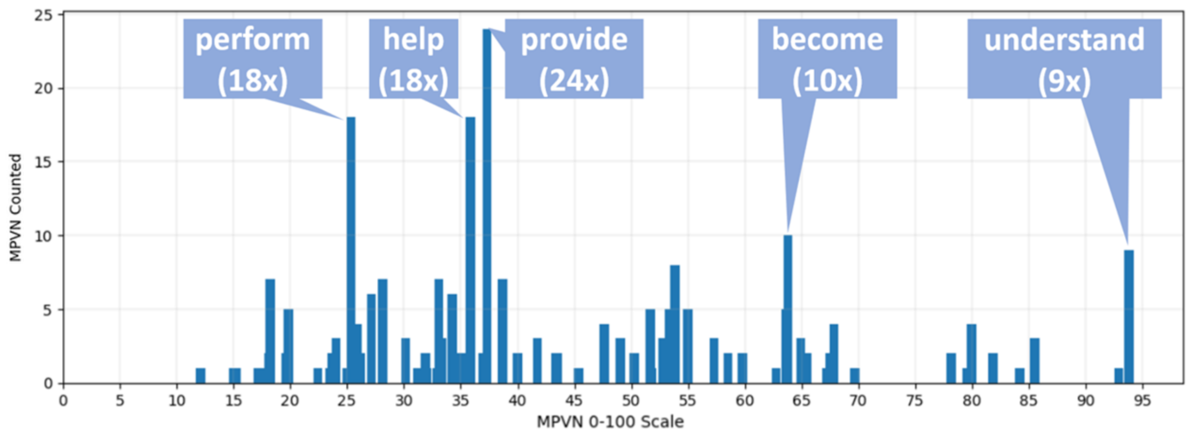

Figure 7.2: Number of MPVN occurrences on the MPVN scale for the scientific company group

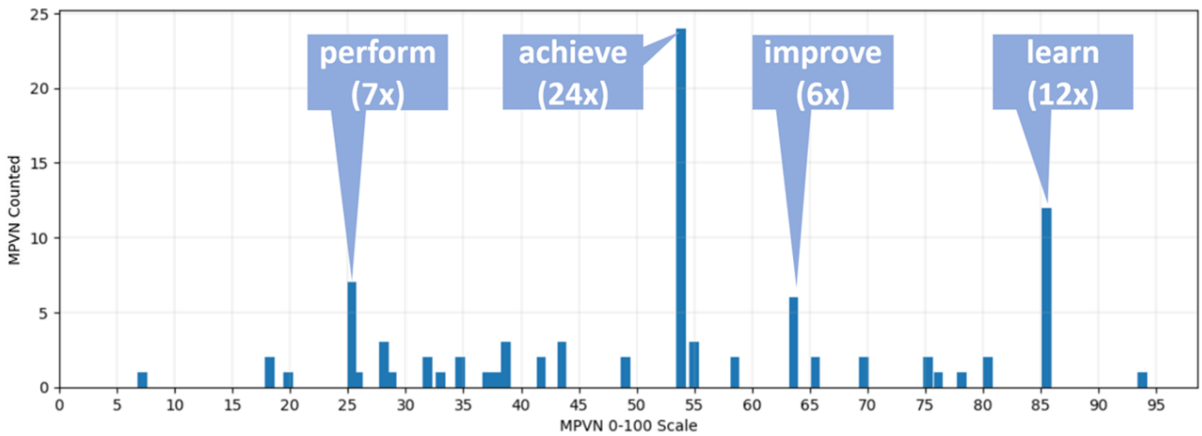

Figure 7.3: Number of MPVN occurrences on the MPVN scale for the scientific OpenAI group

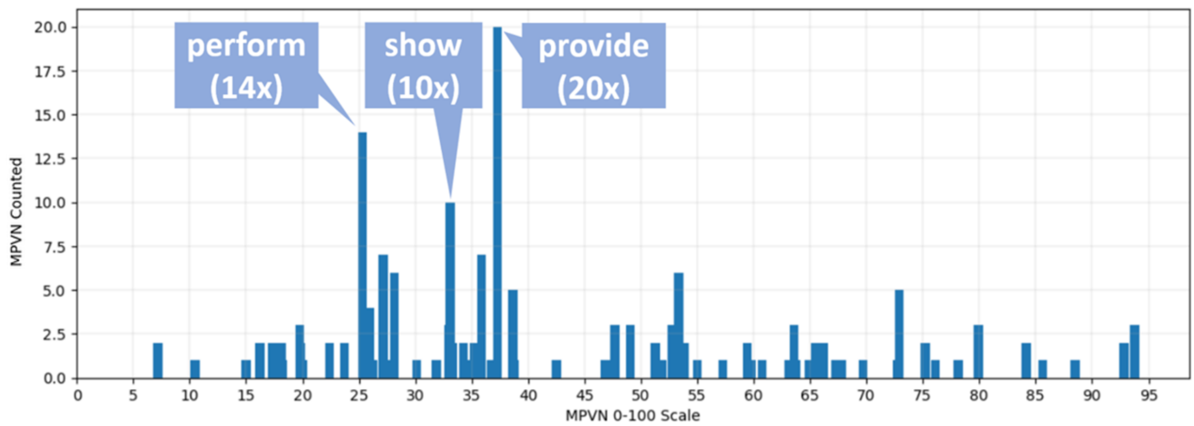

Figure 7.4: Number of MPVN occurrences on the MPVN scale for the scientific university group

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All links were last followed on Dezember 29, 2023.

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

place, date, signature